Management of a high mix production system with interdependent demands: finished goods requirements and raw materials control

by

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Abstract

A product line, characterized by high level of customization, diversification and demand correlation between different finished goods products, requires increased efficiency and effectiveness. The product line, along with the intrinsic correlation, is modeled; the customer expectation is also analyzed. Based on these analyses, two inventory control frameworks are proposed: a fixed service level policy for the raw materials and an optimized policy for the finished goods. The optimal policy is validated using simulation. The proposed policies reduce the inventory value on hand for finished goods and raw materials by 35% and 30%, respectively, while at the same time optimizing the service levels.

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1. Introduction

1.1 Instron Corporation as a Research Environment

Founded in 1946, Instron® is the recognized worldwide market leader in the materials testing industry, holding more than 50% of the market share. The company has various products with all of them sharing production lines. The products cover the following areas of testing: fatigue, tension, compression, flexure, hardness, impact, torsion, spring, test analysis, structural and custom testing. Within each of these categories, many combinations of machines and accessories (hereafter called systems) are possible according to the customer's requirement. That is, all the testing equipment can be customized by the customer. Thus, even the same requirement of two customers may not result in the same order.

Such market behavior forces Instron to keep multiple product lines which further translate into a high inventory, low output factory floor. Thus, Instron serves more than a 'job-shop' volume but at the same time maintains a flexible manufacturing facility to produce highly customized products in minimum time. This issue is clearly visible in the accessories business of the electromechanical division. This area of the production line has the maximum variability and hence is an effective bottleneck. It is well known in the inventory management industry that rather than high demand, it is the variability that is the real reason behind the difficulty in managing service levels (Jemai and Karaesmen [1]). Thus, it is very important to make this area ready for such variability. This can only happen if the right mix of accessories is available at the right time, in the right quantities and at the right place.

Variability is not the only concern while dealing with the inventory in the EM accessories business. There are other intricacies involved which make the problem more challenging. For example, not only can the finished goods be sold as part of a system but they can also be sold as individual after sales parts (hereafter called as OTC - Over The Counter products). Secondly, each system has to wait until all the items in it are available and only then it can be shipped.

Thus, in the case of a system order, there is dependence of demand between these items, and they cannot be viewed as separate entities.

Figure 1-1 – 5800 Series system

The figures show some products offered by the Electro-Mechanical business. Figure 1-1 shows a 5800 Series System. It includes a double column machine with accessories (grips and computers). Orders comprising this whole package i.e. machine with accessories is called a system order.

Figure 1-2 - A wedge action grip

Figure 1-2 shows a similar grip. These grips (and other accessories) can also be sold separately from the whole system and such orders are the Over the Counter (OTC) orders. Figure 1-3 shows different accessories that can be a part of the system.

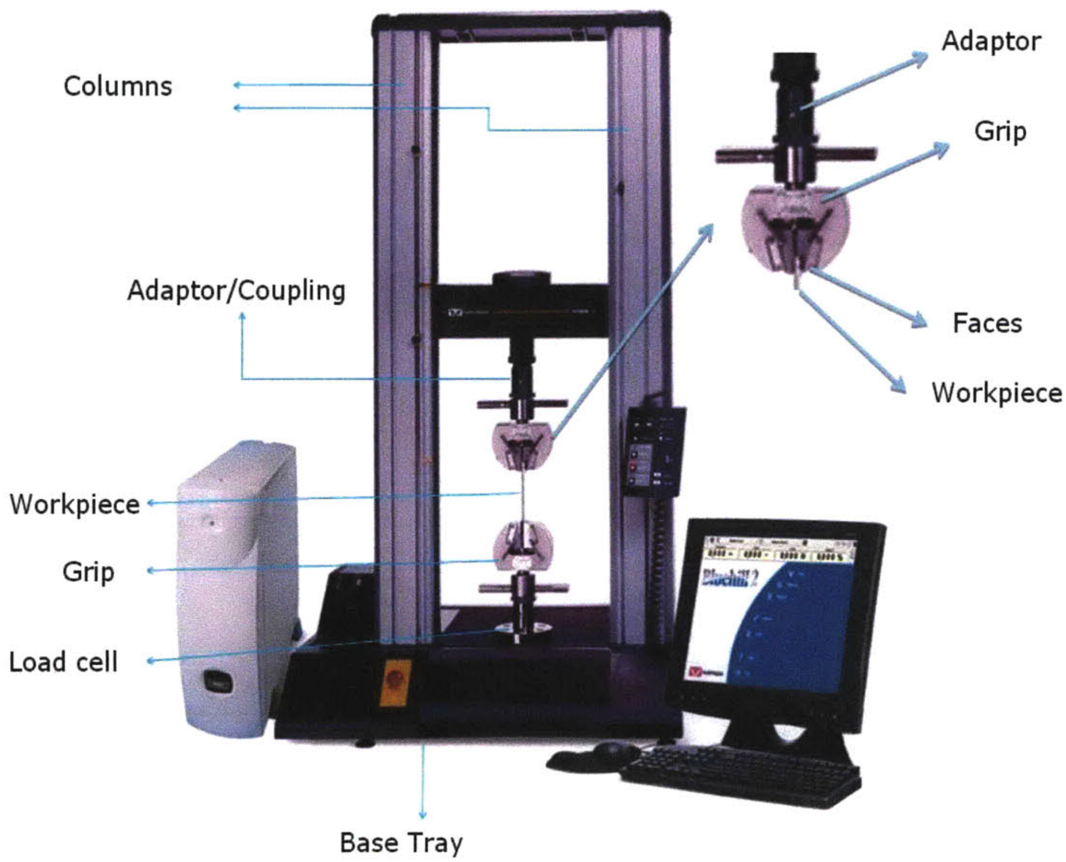

Figure 1-3 - An Instron two column machine with accessories

Currently, Instron holds an inventory value of $4million in the EM area with inventory control based on Distribution By Value (classifying products into categories A, B, C and D according to their cost) and ITW's policy of having a maximum of 2 months-on-hand demand. However, many aspects are neglected while determining their inventory policy- such as demand variability, percentage of lost sales, holding costs and customer expectations. Thus, there is a certain opportunity to scientifically determine the inventory levels taking all the significant factors into account and improving the customer satisfaction by fulfilling more orders as well as minimizing inventory levels.

1.2 Background

Generally, Instron's finished products can be classified into two categories: systems and OTC. In the electromechanical division, both of these categories exist and share a common inventory. Due to the demand variability, the management has decided not to base the inventory control on predicted demand but to switch to a pull production strategy in order to allow production to reorder parts only when finished goods are "pulled" away from the system. The physical implementation of pull production is achieved through the use of Kanban[2] cards for some of the purchased parts and components, and by not stocking some inventory items at all. However, Kanban is not available at the level of final finished goods level yet and has been implemented only 40% at the part level. Some finished goods are currently being replenished according to minimum level reports being generated through the internal inventory management system. This means that the goods are replenished only when a report is run and hence they are more prone to inaccuracies. Some other goods are being replenished by visually seeing on the floor if the quantity drops below a minimum mark, triggering a development order by the area manager. This method too can be inaccurate.

No records for lost orders are kept. Thus, it becomes difficult to determine which item causes the order to be lost. The available data shows only the orders which were fulfilled and hence, it acts as a barrier in determining the optimum inventory level since the actual demand will be underestimated.

The suppliers can also overlap i.e. one item can be bought from two different suppliers. This complicates the case further since there will be two lead times for the same product.

Finally, the final lead time to customer is also hard to determine due to a system audit which takes place on certain products and takes about a day to complete.

Figure 1-4 - Current assembled grips inventory

Currently, sometimes during peak demand, the factory floor gets clogged with the unfinished machines. Also, occasionally, when a whole order is made to wait longer, it gets cancelled, even if just one item was not available.

The markets of OTC and system orders have their own special requirement. While on the system side, the customers are more relenting and are willing to accept larger lead times, the OTC market is more demanding. The customers prefer expedited delivery since they are just waiting for one component in their system. Hence, the OTC market is very competitive.

The system market is usually more relaxed as Instron machines are expensive and they come as a capital purchase for their customers. Hence, the customers understand the large lead times for the machines. For a capital purchase, customers themselves need time to get the money sanctioned from their own organization. This too helps to mitigate the dissatisfaction due to high lead times. For the same reason, Instron starts building the product as soon as it gets an order. However, it does not ship it until all the bills have been cleared.

The systems market helps the OTC market by ensuring that customers buy only Instron accessories which are specifically designed for their machines. Easily available cheaper duplicates require extra adaptors and are not backed up with warranty. Despite this, customers want lowest possible lead times in the OTC products.

1.3 Significance of the Problem

The significance of the project for Instron and the contribution of this study to the literature in the field of inventory management are shown in the following paragraphs.

1.3.1 Significance of the Project

The number of items and parts concerning the Assembly Department is around 1000. In this situation, a great waste of time and money can easily be caused by overstocking. On the other hand Instron's responsiveness to customer demand is identified as an important goal in order to maintain competitive advantage. The optimization of the control parameters is thus critical at the accessories area at Norwood. In order for the strategy to remain optimal in the future, the control parameters must be adjustable accordingly to variations in the product line and in the demand. It is also important that the proposed inventory strategy is easy to apply for the planners and the workers of the facility to properly control the stocking of so many items. The impact of proposing an effective inventory control strategy consists in improved production efficiency and better competitiveness on waiting times which is especially important for the OTC market.

1.3.2 Significance of the Study

This work considers the case of low-volume high-mix inventory systems where customer orders may require several different products (i.e., high customization between products and hence demand between different products is correlated) and the shipment of those items cannot be split. The time delay seen by the customer is the performance measure of concern and the customer impatience is modeled and taken into account: whenever one or more items belonging to an order are backlogged, the customer is quoted a waiting time which is as long as the slowest item's lead time. As the waiting time increases, a customer is less prone to make the order. A continuous review model is proposed using historical sales data rather than using forecasted demand.

Interdependent demands frequently arise in real life multi-item inventory systems. The dependencies of demands for different inventory items may be implied by product options or kits. When the manufacturing lead times for some accessories are long or when customer order assembly time is small, the configuration of a proper mix of items is critical to ensure their availability with the desired probability and avoid order fulfillment delays. Ignoring correlation in the demand when present may lead to two possible consequences: stocking more than necessary or not being able to provide the desired service level. It is demonstrated by R. Zangh that this assumption leads to an overestimate of the total time delay when items are actually correlated [2].

Unfortunately most inventory models on time delay in the literature assume one-item orders. The resources available in the literature which consider interdependence in the inventory planning can be split in two main categories:

- Studies about joint replenishment take advantage of the correlation of the demand to minimize the ordering or setup costs and transportation costs. Unfortunately these techniques are not useful when items are provided by many suppliers. As described in the Introduction, for what concerns the case studied here, accessories are both manufactured in-house as well as ordered from a large number of outsider suppliers.

- A small number of studies describe similar problems but under different conditions. In particular some of them assume that parts belonging to the same order can be shipped separately to the customer if some item is not immediately available. Other works consider other inventory control models.

1.4 Review of Prior Instron projects

In the past ten years three MIT graduate students have completed research internships at Instron working on inventory control and operations management. The theses of D. Wheeler, G. Caterino and H.T.Nguyen are outlined below.

The purpose of Wheeler was to optimize the EM grip inventory by applying queuing theory, optimization techniques, supply chain rationalization and simulation models [3]. In particular the author, together with a project improvement team, achieved a thirty-percent reduction of the inventory for the 56 EM grips belonging to the Instron product line at that time. They implemented a pull production in the grip assembly job shop by setting up stock shelves for finished goods and components within the shop from which the parts were removed to fill the orders. When the level of finished goods drops below a specified quantity (the reorder quantity) the mechanic is signaled to replenish it. Moreover as the components to build the grips, which are drawn from the bins on the shelves, drop below the reorder point, the planner receives a signal and replenishment orders are placed. Reorder quantities and lot sizes for the finished grips and some components were provided by the Economic Order Quantity (EOQ) and the continuous review (Q,r) models. These models were applied on the most significant components which had been identified by applying the Distribution By Value (DBV) technique (Silver, Pyke and Peterson [4]). Items were classified as belonging to three different Classes (A, B and C). The most valuable components (Class A and B) were placed under the Q,r control policy, while reorder quantities and reorder points for items belonging to Class C were set respectively to one year's supply and six months' supply for each item.

The second thesis objective was to improve the responsiveness and flexibility of the assembly process applying elements of Lean Manufacturing (Caterino [5]). With the use of Kanban control in assembly, daily production schedules based on demand rate and decision rules to guide the work process, the assembly throughput times have been reduced by 40% on average in the final assembly operations. Changes to the physical assembly environment have been made in order to increase flexibility of the output. The author proposes an inventory policy to coordinate in-house inventory levels with manufacturing demand and improve the coordination with external suppliers. The policy, similarly to Wheeler's work, is based on a (Q,r) model and DBV and is tailored on a small number of finished goods items (three selected product families). Its application on a pilot process showed a 15% reduction in the required floor space for an equivalent manufacturing output.

Nguyen in his work has tried to improve the service level by implementing lean initiatives in the plant [6]. Root cause and Value chain analysis were carried out in the plant to find opportunities for improvement. A material replenishment model was proposed that would help the company effectively pull parts from the suppliers. Lot sizes were determined according to extended economic order model quantities adjusted using Lagrange multiplier to account for multiple parts being manufactured at the same time. For the inventory control, continuous review policy is proposed for the EM business so that low safety stock can be kept and probability of stock out can be reduced.

In the next sections, the problem has been cleared defined qualitatively and quantitatively. Literature review for the work has been summarized in the next section. It highlights all the text that was helpful in understanding and interpreting the problem better. Next, the methodology to study the problem has been introduced which introduces the thought process used to develop the approach and then the steps that were followed, how data was collected and how it was interpreted. Finally, the problem was solved using the method highlighted in the above mentioned section and results obtained. These results after proper validation are discussed in the results section with some recommendations.

2. Problem statement

The project goal, shared among the four group members' theses, is the definition and implementation of an inventory control framework for the EM accessories stored in the Norwood facility. The result of this work is enabling the inventory planners of the Configuration Department to stock the optimal mix of accessories in order to guarantee a satisfactory service level to the customers and minimize the inventory cost.

2.1 Project Objectives

The project specifications provided by Instron are listed below.

1) Analyze the accessory level offerings based on customer demand and sales volume.
2) Determine finished goods inventory level for each accessory.
3) Develop and implement an internal finished goods replenishment model based on a *pull* strategy.
4) Coordinate with Supply Chain group to insure Kanban quantities support for the finished goods model.
5) Identify and procure any needed tooling.
6) Determine and implement any layout changes.
7) Measure and monitor results.
8) Make it visual and involve factory employees.
9) Identify key performance indicators.

2.2 Designing the Optimal Inventory Policy

In order to meet the specifications, the problem has been modeled and its critical elements have been identified.

A first challenge for this project comes from the large amount of accessories to control: more than 800 finished goods concern the Configuration Department and include grips, fixtures, faces, extensometers, couplings, adaptors, computers etc.

Some of them are assembled in the Norwood facility, while some of them are purchased parts or assemblies. The large number of components that constitute each finished item and the large number of vendors that supply Instron represent a further source of complexity for the analysis.

In the previous theses performed at Instron, a simplification of the large amount of parts considered was provided by Distribution By Value (DVB) and 80/20 techniques, which are described in Chapter 4, allowing the authors to focus on the most significant ones in terms of value or profitability. Since the 80/20 analysis is a currently widely used and appreciated tool within the company, the team decided to adopt it to perform an analysis of the demand, measuring volumes and profits.

As described in the Introduction, demand has two components: Systems and OTC. This allows the problem to be split in two separate analyses.

For OTC accessories customers expect immediate shipment. Since the OTC market is more sensitive to competitiveness, an effective control strategy is critical to provide customers with a satisfactory service.

The Systems market, instead, is characterized by longer waiting times expected by the customers and less external competitiveness. However all the parts of the machine must be shipped together, with rare exceptions, and if a part is missing the order is delayed. In fact most of the times customers cannot perform their tests if a part is missing, and in every case splitting the shipment of an order is costly and not desired by the company. In 2008 no more than 4% of the Systems orders got split and this percentage is meant to decrease.

While the OTC market can be analyzed considering individual profits and volumes for every item, an accurate model of the Systems demand should take into consideration the inter-correlation among products. This suggests that the demand analysis for systems should also account for the importance of an accessory as purchased together with critical items. The *Virtual Profit* is an index based on combined profits developed by the team to model the inter-dependence of the demands and it is presented in the paragraph 4.3.2.

Since the waiting time expectations for the two markets are different, the inventory levels for the same items must satisfy the two demands. The problem can be thus decomposed in two analyses for the different markets. Once both the stocking quantities are set for both demands a risk pooling strategy can be implemented by aggregating those results.

For both the markets, once the 80/20 analysis has provided a measurement of the criticality of the items within the product list, the proper inventory control policy for the items must be identified. Constraints to this project are given by the fact that the Norwood stocking capacity is limited and the inventory allowed by the Instron management is less than 2 MOH[1] (Months on Hand) for every item. Thus in order to maximize the customer satisfaction and so the profit, the basic strategy is implementing two different control policies for two different classes of accessories:

- The most critical items will be assembled or purchased to stock so that high service levels will be achieved.
- The less profitable items will be assembled or purchased to order, minimizing their inventory costs.

However the optimal division between items deserving to be stocked and items that will be made to order needs to be found. Another parameter to be set is the desired *Type I service level*, or percentage of customers that will be immediately served, for the first class items. Wheeler [3] suggests to favor the "80" items (those items that concur to the 80% of the total profit/volume or Correlation) and provide them with 0.95 Type I service level. Unfortunately there are two reasons why this is only a suboptimal solution:

[1] Months on Hand = 12 (Average Inventory Value on Hand / COGS)

- The 80/20 curves usually show one or more steps in the distribution of volumes or profits, so that the division between most important and less important items is quite clear. This is also valid if the quantity measured is the Correlation. However the step does not necessarily occur at the 80% of the cumulative profit: its position can vary depending on the situation. Setting the threshold at 80% would lead only to a suboptimum.

- The 0.95 Type I service level was set accordingly to the Instron management which found it reasonable. However assigning a constant service level for all the make to stock parts is certainly not the optimal strategy.

This issue can be addressed designing an optimization problem which would allow splitting the items in the two classes in an optimal manner, setting at the same time the service levels for the for the first class items.

There are several factors that the problem must take into account. Firstly storing parts has a cost in terms of space, handling and cash blocking, in general referred to as *holding cost*, which has to be minimized. Moreover there are items which are more worthy to be stored than others because give a larger profit (on their own or being sold with other items). In order to consider the described issues the stock level for each item i will be determined by maximizing the expected total profit generated by that item. A model of the expected total profit is given by the expected revenue minus the expected total costs.

The expected revenue for each product can be found by multiplying its unit cost by its expected sales $E(S_i)$, which are a function of the demand rate and the number of items in stock. Note that the past and future expressions of the demand are not available since the sales lost because of the waiting time quoted are not registered and forecast is not used at Instron. Historical sales are the only information that can be found. For the purpose of this project we assume that the expected demand is equal to the past sales. The effects of this assumption are mitigated by the pull strategy that (Q,r) represents causing the actual demand to drive the inventory control once the control parameters are chosen.

Moreover, since customers are willing to wait a variable amount of time if the parts are not immediately available, sales are also function of the *delay acceptability* w_i, or the percentage of customers that would still buy the item if it is not in stock.

Currently, the production lot sizes or reorder quantities are determined based on their value and historical demand without taking into consideration the lead times. Though suppliers have a negotiated contract with the company, they are usually supportive of the lot size requirements. In order to guarantee the selected service levels to the customers, one of the components of the solution consists in making sure that these quantities are enough to satisfy the demand over lead time with satisfactory probability.

Finally, the raw materials control is evaluated. Based on the finished goods production, the raw materials inventory control has to be synchronized and the parts have to be available with high probability. An optimized policy is proposed in order to guarantee the necessary support to the finished goods replenishment model. The optimized policy requires knowing the suppliers' replenishment lead times; this requires data collection and accuracy. The raw materials control is evaluated by comparison with the current policy.

The resulting optimal strategy is evaluated in its costs and benefits: a simulation tool is designed in order to test and validate the control policy and compare it with the current situation.

In order for the finished good inventory policy to be implemented and utilized by the Instron workers in the future, the control parameters must be periodically computed and adjusted. For this reason the analytical tools used for this work are designed for reusability and robustness, as well as easiness of use and compatibility with the data and tools available at Instron. The tools must take into consideration adjustments for new products introduced in the product line and for dismissed ones. In fact the introduction of a new series of accessories with a partial substitution of some old one has occurred this year and can occur again in the future. The implementation of the strategy in the Configuration Department, including the physical arrangement of the stock bins and the Kanban cards, and the training of the workforce are part of this work, are part of this work, in order to guarantee that the strategy is correctly understood and continued.

3. Literature Survey

3.1 Introduction

Since our first contact with the problem, it was clear to us that its set of features and objectives made it a very particular challenge. The theory we learnt from classes and from Simchi-Levi et al. 2000 [1] guided us to the choice of a (Q,r) policy but the standard set of assumptions used to determine the parameters Q and R did not fit our problem. In particular the correlation between the demand of the various products, the fact that many items could be sold both alone and in a system order, the fact that a system order cannot be shipped unless all the items are available and the fact that customers have different expectations on acceptable lead times for different items required a new approach to solve the problem. Many of these challenges are somehow considered in literature but often with a different objective and anyway, to our best knowledge, they have been never considered together. In 3.2 we briefly discuss the vast literature about the (Q,r) policy which constitutes the basis of our work; in 3.3 we present papers which faces the demand correlation issue; in 3.4 we argue about the usage of some papers regarding the customers' expectation issue; in 3.5 some references about simulation are presented.

3.2 The (Q,r) Policy

In those cases in which the inventory is reviewed continuously (in opposition to periodically) a heuristic control policy which has been well-studied in the last several decades is the so called "Q,r" (sometimes also named r,Q or in other ways). The basic idea is that whenever the number of items held in inventory drops to or below r an amount of Q units of goods is issued to replenish the system. Hadley and Whitin 1963 [8] present an exact solution to the problem when there is a known penalty cost assessed on each unit backordered and they provide, under some assumptions, two approximate iterative heuristic solutions.

During the following decades the Q,r policy has been extensively explored in literature, many of the original assumptions have been relaxed and many of its properties proved.

In particular important convexity results are given in Zipkin 1986 [9] and Federgruen and Zheng 1992 [10] and the existence of such results justify the research of optimum values. Also, interesting convexity results are proved in Wang and Li 2007 [11] for the discrete demand and inventory case.

3.3 Correlated demand and the inventory management problem

3.3.1 Correlated demand and job-fill rate

Demand correlation among different items and its effect on inventory policies is a key aspect of this work. Even though it is common in real-life multi-item inventory systems, this phenomenon has not received a large attention in the existing inventory literature. We were able to find some papers related to the problem we are facing but none of them could directly be used in this case either because they pose different objectives or they are firmly based on a set of assumptions which does not apply to Instron case.

One of the first papers to focus on similar problems is Smith and Chambers 1980 [12]. In such work in fact it is introduced for the first time the concept of "job-fill" (in opposition to "part-fill") rate criterion in this context. The paper deals with the determination of the appropriate collection of parts to be carried out to repair a machine. As in our case if only one part is missing the order cannot be completed (the machine cannot be repaired). In that case the cost associated with not being able to complete a given job due to unavailable parts is related to a longer downtime for the machine (the repairer has to go back to the warehouse and return on site again), in our case it is tied to the customer unsatisfaction and the resulting risk of losing the order. Such problem was already known at the time as the "fly away kit problem" or the "submarine provisioning problem", however these previous papers traded off shortages against part-fill rate instead of order-fill rate. Smith and Chambers [12] is then an interesting article but doesn't consider all the issues present in our case because the correlation is not considered as the failures of different part types is assumed to be independent. However, other than for the "job-fill" rate criterion, [12] is very useful to us also for a theorem about the importance of ranking the items before considering an optimization problem.

Using Smith and Chambers' "Job-fill" rate criterion, Zhang 1999 [13] studies the expected time delay in multi-items inventory systems. In such paper the demand is assumed to be correlated across items and customer satisfaction is measured by the time delays seen by the customers. As a result, an exact expression for the expected total time delay is derived. Also, it is shown that when items are actually correlated, assuming items are independent leads to an overestimate of the total time delay. This however assumes that the parts can be sold separately if some of them are not in stock. In this sense it is shown that demand correlation is in fact an opportunity that should be exploited. In our case, because an order cannot be shipped unless all the parts are available, the demand correlation is an issue.

3.3.2 Correlated demand and joint replenishment

The point of view presented in [13] is common to many other papers that deal with correlated demand. In fact many papers who consider demand correlation are focused on joint replenishments policies such as Liu et Yuan 2000 [14], Feng et al. 2007 [15] and Tsai et al. 2009 [16]. In particular [14] specifically considers the can-order policy for a two-item inventory system with correlated demands. Unfortunately joint replenishment doesn't specifically help with the problems that Instron want to solve in its EM department and, even though it can still be beneficial, its usage would add a large amount of complexity and would allow very small benefits, if any. In fact, as regards items manufactured outside the company Instron has a very large number of suppliers and buys from each of them a very small amount of different products. Moreover, as regards items manufactured inside the company, very small setup costs are involved and the assembly is mostly make-to-order. In other words in the papers which focus on joint replenishment the objective is reaching a balance between ordering costs, storage costs and stockout costs while in our case ordering costs are not significant. The same considerations about joint replenishments also apply to [15] and [16]. Specifically, [15] formulates the problem as a Markov Decision Process and focuses on joint replenishment and correlated demand, proposing a moving boundary based policy and comparing it to other control policies. Tsai et al. [16]

instead propose a clustering algorithm to deal with demand correlation which is similar to a first possible solution, later abandoned, that we considered to solve our problem. Such paper claims that it is difficult to define the demand correlation between items, especially when the number of items increases and for this reason a clustering algorithm is proposed. Such algorithm is used to find an optimal clustering result which is used to determine the parameters of a can-order policy in presence of joint replenishment. The result is then tested through simulation and sensitivity analysis, two steps that are fundamental also in our approach.

3.3.3 Previous work with different assumptions

As said the literature which deals with correlated demand is relatively small and a good part of it is focused on joint replenishment which is not useful in our case. However, some papers are closely related in their intent to our work, although not directly applicable due to different assumptions. Hausman et al. 1998 [17] has very similar problem statement to our as it is said that the objective is to "configure a proper combination of component item inventories so that availability of component items is ensured at pre-specified levels to avoid order fulfillment delays". Unfortunately this paper considers a periodic review order-up-to policy and so is not compatible with continuous replenishment. Anyway the paper contains some very interest ideas and some theorems and lemmas which can be considered also in our case. Very close to our objective is also Wang et Hu 2008 [18] which studies the application of a (Q,r) policy with budget constraints and optional components. The budget constraints, at least in the way they are formulated in [18], are not of primary concern in our case but the approach proposed is still very interesting. Unfortunately, two of their assumptions are not verified in our case: it is not true that the payment is due at the time an order is placed (but this problem could be overcome) and most importantly it is not true that the customer will purchase a system without optional components when the optional components are out of stock. Optional components are in fact, in the majority of cases, necessary to use the Instron machine and no one would buy a machine without them.

3.4 Customer defection

In this work, the effect of customer impatience (or *defection*) on the inventory performance is studied. Two main contributions on this field are used as references: Gershwin et al. 2009 [19] and Veatch [20]. The main reason why this work investigates the customer impatience is that the number of orders filled (in literature *Type II Service level*) depends on how many customers would wait for a product if it were not in stock. In particular, the number of filled orders is the sum of the number of orders filled immediately plus the number of orders completed because the customers decided to wait and not to cancel the order once they were quoted a lead time.

In [19], a manufacturing firm that builds a product to stock in order to meet a random demand is studied. If a product is not in stock and orders cannot be met, customers are quoted a lead time that is proportional to the backlog, based on the production time. In order to represent the customers' response to waiting, a *defection function* - the fraction of customers who choose not to order as a function of the quoted lead time - is introduced. The defection function is then used to obtain the optimal production policy, which results in a hedging point form. One family of defection functions is studied, a sigmoid function of the form:

$$B(x) = \frac{1}{1+e^{\gamma(x-\eta)}} \tag{3-1}$$

This expression for the defection function is then used to model the system behavior, and will also be used in this work. However, an additional important conclusion is that numerical results suggest that there is limited sensitivity to the exact shape of B(x). Furthermore, the precision of the defection function is limited by the intrinsic approximate nature of what it models, i.e. the customer impatience.

In [20] the same production model, in which the customer is quoted a lead time depending on production time and backlog, is presented as a "nuanced model" of customer behavior, compared to the two extreme models of complete backordering and lost sales, where all the customers either wait or not. One particular production model is considered: a continuous one-part-type, single machine model with Markov modulated demand and deterministic production is considered. Using this particular model, the impact of customer impatience is shown to be captured by one quantity, the mean sojourn time in the backlog states. As in [19], the optimal quantity has hedging point form.

Based on the particular model considered, Veatch shows that the effect of customer impatience can be captured by the only mean sojourn time in backlog, and this simplifies the problem of obtaining an optimal production policy. Given that the effect of customer impatience is captured by the above mentioned quantity, in fact, other simpler customer behavior models can be used, and still the optimal policy is reached.

This thesis analyzes a different model: only some of the products are produced in the factory floor, while most of them are ordered from suppliers. Moreover, the replenishment lead time is random and constraints on the reorder quantities have to be considered. Thus, the assumptions made in [19] and [20] are not valid any more, and the optimization problem is different. Moreover, the two papers do not present any attempt to shape the defection function in the actual industrial application. However, the analyzed work gave some useful insight into the modeling of customer impatience. The suggested sigmoid form is used in this work, and the limited sensitivity to the exact shape of the function is considered. Finally, this thesis considers the use of company-wide surveys in order to shape the defection function to the needed precision level.

3.5 Simulation

Simulation has been used as a validation tool in this work. Monte Carlo is one of the simulation techniques used to validate our results. The principle behind Monte Carlo simulation is that the behavior of a statistic in random samples can be accessed by the empirical process of drawing lots of random samples and observing the behavior (Mooney [21]). However, care has been taken while generating customer demand. Truncated normal distribution is used to generate demand since it should not go negative in the cases when the coefficient of variation is high (Strijbosch and Moors [22]). Coakley and Carpenter 1983 [23] have used Monte Carlo simulation to predict final system behavior when it cannot be directly predicted from the inventory models. They validate the model before running the simulation using constant values and matching them with theoretical results. Finally, they use the simulation results to analyze different conditions such as relaxing theoretical constraints and getting the inventory levels.

Jung et al. 2004 [24] have presented a method to determine safety stock levels, which further effect the customer satisfaction levels (service levels), using a computational framework for planning scheduling applications in realistic supply chains. They use simulations to optimize their results when faced with improving customer satisfaction, holding costs and production constraints. Inside the computation for optimization, repeated simulation of the supply chain takes place over the planning horizon, each with given Monte Carlo demand samples. Then, within each of these simulations, a series of planning and scheduling optimization problems are solved.

Grange [25] in his paper pays particular focus to demand distributions of slow moving items. He finds out the misidentifying demand distributions can have a detrimental effect on the fill rate leading to high and lower rates depending on over and under estimation of right tails. He also adds that multi-SKU inventory compensates misidentification by reallocating investment relative to the costs and expected demands of all the SKUs. We have thus, taken particular care in finding out the demand distribution in our case, as highlight in the methods section.

3.6 Conclusion

The problem this work deals with is a particular one and a solution tailored for this case cannot be found in literature. Not many authors focused on demand correlation in multi-items inventory systems and many of them consider a rather different set of assumptions thus being allowed to see it as an opportunity to be exploited using joint replenishment. A few papers which consider a similar problem statement are still not applicable to our case because they differ in some fundamental assumption such as periodic inventory review and optional nature of accessories. Also as regards the customer impatience issue the papers analyzed do not provide a univocal methodology to be used in our practical case but they contain very interesting ideas and results. Simulation was also found to be frequently used both as tool to find a solution and as tool to validate the result found with another method.

In conclusion our problem requires a new solution in order to deal with all its features but the existing literature constitutes a fundamental basis to our work with its ideas, theorems, reasoning and methods.

4. Methods

4.1 Choosing the right methods

The goals of this project are described in detail in chapters 1 and 2. One sentence summarizes them effectively: "having the right mix of products on the shelves at the right time". As mentioned before, this involves searching an optimal inventory control and production policy by considering all the products together, especially taking into account the system orders, thus the correlation among items' demands.

The significant number of items involved and the differences in their supply chains added high levels of complexity to the project. Not only do we want to have the correct "mix" on the shelf, but the implementation of the derived policies will differ depending on the product's type and supply chain. Furthermore, using one's own judgment on each SKU would not provide the company with a repeatable strategy. For these reasons, general and parametric methods always have to be used.

In addition to the optimal policies, important results of the project come from the analysis phase (demand analysis, correlation analysis, customer defection, 80/20). The produced documents, indeed, are important in providing the manufacturing, sales and marketing departments with sources of data which allow effective strategic planning. As an example, knowing which products are often sold together in the last two years, could suggest marketing already customized systems (composed of the products often sold together); if this operation is successful, the company could focus its investment in the inventory for a limited number of products, holding less risk associated with other products. Moreover the results of the analysis performed by the team and provided to the company find an application in the identification of products to discontinue because of their scarce profitability and importance within the product list.

What is more, in each sub-issue addressed by this thesis, the purpose is not only identifying the optimum (optimal inventory control policy, optimal replenishment levels) but also proposing the so called *"good enough"* solution. As widely happens in manufacturing and operations management, in fact, the application of systematically searched optimal policies holds a level of complexity that is not worth the investment. For instance, considering the optimal replenishment methods, agreeing with the suppliers on the optimal reorder quantities for a product could not be feasible or could involve additional investment, and using a QR policy implemented with Kanban cards, that are already used, would be more easily and quickly implementable than different policies that could guarantee a relatively small increase in expected profit.

In conclusion, the work described in this thesis is meant to produce data analysis reports and suitable solutions for the inventory control policies of a significant number of products. This chapter describes the steps that are undertaken in building the analysis reports, in designing the control policies and in collecting the necessary data for the policies to be implemented. The methods used in each step are briefly described in the following paragraphs and then explained in more details in the following chapters.

4.2 Main steps followed

Figure 4-1 shows the main steps involved in the project. Every independent task is represented by a blue filled circle, while the developed software tools are represented by smoothed rectangles. The arrows indicate task scheduling requirements. As an example, let us consider the following tasks: comparison, individual demand analysis and correlated demand analysis. In order to perform the comparison task, the results from the individual and correlated demand analysis are necessary; thus, these two tasks need to be finished in order for the comparison task to be performed. The diagram is a modified version of the PERT diagram which does not show the duration of the tasks.

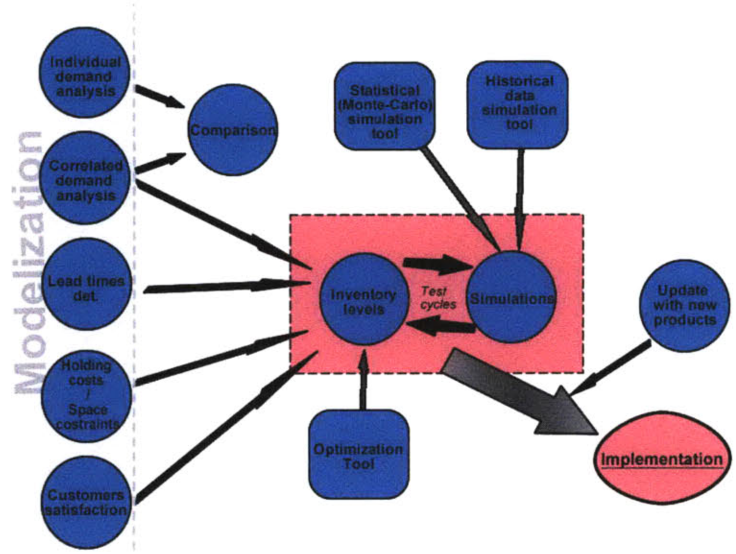

Figure 4-1 – Tasks diagram

As previously mentioned, the main outcome of the project consists in data analysis reports and recommendations for inventory control policies. The most important reports are obtained in the steps *Individual demand analysis*, *Correlated demand analysis* and *Comparison*. In these three steps, demand analysis of all the involved products is performed, at first simply by volume and profit, and then considering how they correlate to each other. Finally the results are collected in a Comparison report, meant to underline the importance of the correlation. The step *Inventory level* involves designing the control policies, while the performance of these policies are estimated in the step *Simulations* and implemented in the step *Implementation*. The importance of these two final steps is highlighted by the orange box in the diagram.

The left side of the diagram shows the steps needed in modeling the system. In order to design the inventory control policies, the following information is needed: lead times for each product, profit and correlation analysis, holding costs, space constraints and a model of the customer satisfaction. All this information builds the model of the system, used to find the optimal solutions.

The remaining part of this chapter describes the goals of each task, the approach to it and the methods used.

4.3 Explanation of the tasks

4.3.1 Individual demand analysis or Pareto analysis

This task involves analyzing the orders placed in 2008 and 2009. The list of orders, together with the associated quantities and prices, is used to perform a demand analysis based on both profit and volume. The purpose of this analysis is to find the most important products and the least profitable ones. The results are useful to the company in showing the updated data on volume and profit made by the products during the last two years.

The *Pareto principle* (also called *80/20 principle*) is a heuristic principle that is often applied in analyzing profit and volume in operations management (the Pareto analysis). Applied to profit, it states that about 80% of the profit of a company is made by only 20% of the products it sells. The products belonging to that 80%, which are the most profitable ones, are called the *80s*, while the remaining products are the *20s*.

For the purpose of this analysis, the products are divided in six different categories: grips, fixtures, faces, coupling and adapters, compression anvils and anvil sets and other accessories. The first step of the analysis involves summing up the profits made by each product in all the orders and determining the total quantity shipped in each year. A report has been given to the supervisor, in which the most profitable items were identified through the Pareto analysis. In addition to this, the least profitable items were highlighted in the report: all those products which belong to the bottom 1% of the profit or were sold at most twice. This result is important to identify items eligible to be discontinued. However it does not provide a measurement of their criticality within the product list. The Correlation analysis, described in 4.3.1, provides a more accurate result.

For a more expanded discussion of the Pareto analysis, please see Chapter 5.

4.3.2 Correlated demand analysis and Comparison

As mentioned earlier, the design of the optimal policy is complex because it has to encompass a very high number of different accessories that are often sold together in the system orders (when customers buy a machine and choose a set of accessories with it). Moreover, the above mentioned individual demand analysis is less accurate than necessary because it does not take into account the system orders.

As an example, two products X and Y can be considered. If X is an "80" item and Y is one of the lowest profit items, the individual demand analysis would suggest holding less inventory for item Y or even making it to order. By considering the system orders, however, we could find out that product Y is often sold together with X, and is less profitable because it is discounted or relatively less important. Holding lower inventory levels for item Y would then be a losing strategy, because it would block the orders of X and create additional profit loss.

In this project, the correlation between different products is considered in designing the control policies. The goal is obtaining a profit indicator which quantifies the profit made by each product if in stock, or quantifies the loss realized by not having it in stock for a given period of time. A MATLAB function, using the IBS reports with all the orders of 2007 and 2008, calculates how many times each product is sold with any other item and quantifies this expected profit.

New profit indicators were obtained considering the correlation, and a new analysis report was generated (step *Comparison*). This report shows what are the most profitable items and what are the ones which are still in the bottom 1% of the profit after considering the correlation. As mentioned in paragraph 4.3.1, this report completes the analysis of the items to be discontinued, together with the 80/20 report.

For a more expanded discussion of the correlation analysis, please see Chapter 5 in Maria Carolina Serra's master's thesis [26].

4.3.3 Lead time, holding costs and space constraints

These three steps involved data collection, which is necessary to design the control policies. The data collection methods, including holding costs and space constraints, are further explained in chapter 4.4 of this thesis.

By working with the supply chain managers and using the IBS tracking system, at first we tried to obtain a list of lead time values for all the products involved in the project. The term "lead time" was used in a more general sense, indicating replenishment lead times for purchased parts, manufacturing run time for manufactured or assembled parts, and collecting time for catalog numbers that actually are a kit of items. In general, the term, lead time, indicated the total time needed for a product to be again on the shelf when required.

4.3.4 Customer satisfaction

In order to maximize the expected profit, the loss for a part not being on the shelf has to be quantified. Let consider the case, however, in which one particular SKU is not on the shelf. The customer would learn that a particular product was not on the shelf and that the total waiting time would be n weeks. Would he still go on with the order? And what if the order request was actually for a system including that product?

In general, there will always be a number of customers who will still buy a product even if the order cannot be fulfilled from stock and a longer waiting time is quoted. This percentage depends on the product and on the type of order, and is a function of the quoted waiting time. This function is referred to as "customer defection". The literature background about customer defection is discussed in chapter 3.

Obtaining this quantity from the data or in any rigorous way is not feasible due to the following reasons:

- Lack of hard data about lost sales

- Customers have different interests, priorities, concerns

- Other reasons (human behavior, complex products interdependence)

Thus, a reasonable estimate is obtained through a survey directed to the sales people, who work on orders with the customers. The starting expression of the customer defection function is a sigmoid, as discussed from the literature, and the function is further shaped by asking general questions and looking for ranges of values through the survey. This function represents the percentage of customers still willing to wait depending on the waiting time that can be offered on one particular item.

For a more expanded discussion of the customer defection analysis, please see Chapter 6.

4.3.5 Inventory levels

This task involves designing the production and inventory control policies for both finished goods and raw materials.

Two main types of policies are used: make to stock and make to order. The less profitable items will hold lower service levels or be made to order, while for the remaining products stock levels are determined. The choice of the MTO or MTS policy for each item is based on optimizing the profit, and is described in *4.3.6.*

The most suitable make to stock inventory control policy is the QR policy (or *reorder quantity*). One reason is that the inventory at Instron has always been managed through two quantities: the so called *minimum quantity*, corresponding to the safety stock, and the reorder quantity. Even if these quantities were obtained with rules of thumb, they are used to set a safety stock level and reordering when the levels go below the minimum quantities. Moreover, an increasing number of parts are being managed by *Kanban cards*, which is an automatic inventory replenishment method. When the inventory level reaches a minimum quantity, the corresponding card is put on a board and it will automatically trigger the order of a predetermined release quantity from the suppliers. This system is easily updatable once the new optimal values for Q (reorder quantity) and R (reorder point) are derived.

The reorder quantities are determined in such a way that they cover the demand over lead time with a probability of 99.87%, still satisfying eventual constraints on the lot sizes. The optimal reorder points, on the other hand, are calculated from the lead times, the average demand, the values of Q and the desired service levels. While lead times and average demand are obtained in the data collection phase, the service levels represent our degrees of freedom in designing the policy. For the finished goods inventory, these levels were chosen by optimizing the profit, as described in *4.3.6*. The raw materials inventory control, instead, is designed in such a way that the service levels are always high, in order to support the finished goods production.

For a more expanded discussion of the raw materials inventory control, please see Chapter 7, while for the finished goods inventory control see Alberto Facelli's master's thesis [27].

4.3.6 Optimization

The available degrees of freedom in designing the FG inventory control policy are given by the service level corresponding to each item (Type I service level, defined as the percentage of time the inventory for a certain item will not be empty, thus being able to meet demand) and whether each product will be made to stock or made to order (MTS or MTO).

These choices are determined by solving an optimization problem. The goal function is the total expected profit, defined as total expected profit coming from sales minus the inventory holding costs. The total expected profit coming from sales is calculated considering the correlation between products in the same orders (as described in *4.3.2*), while the inventory annual holding costs per item are multiplied by the expected inventory levels in the QR policy.

The result of the optimization tool, implemented in Matlab, is a list of optimal service levels for all the items. If the optimal service level for a particular product is lower than a certain limit than the final suggestion for it will be a make to order policy.

For a more expanded discussion of the finished goods policies optimization, please see Alberto Facelli's master's thesis [27].

4.3.7 Simulation

An important step in studying the optimal control policies is the simulation phase. It allows us to test the designed strategy in order to check its feasibility and to estimate its performance measures (actual service level obtained, months on hand of average inventory).

The simulation tools are used both as design aid and as final performance measurement that helps in selling the proposed recommendations. The simulations are implemented in two different ways: at first simulating random demand with a discrete probability distribution with the actual mean and standard deviation (plus intra-quarter growing average), then by using the actual historical data. The former tests the policy for robustness with a more general background; the latter shows a comparison between the results of the proposed policy and the current one.

For a more expanded discussion of the simulation of the proposed policies, please see Samarth Chugh's master's thesis [28].

4.4 Data collection methods and IBS

Most of the tasks undertaken in modeling the system involved hard data collection from the databases of the company. Referring to the diagram in picture 1, these tasks are:

- Individual demand analysis;
- Correlated demand analysis;
- Lead times determination;
- Holding costs / Space constraints;
- Customer satisfaction;
- Historical data simulation tool;

- Update with new products.

The holding costs are obtained from the operations manager and head of manufacturing and through some financial research on cost of capital; the space constraints are estimated talking to the managers and exploring the factory floor. The information about the new products (new item numbers, discontinued items, updated demand forecast) was obtained from to the engineers in charge of the corresponding projects.

The model of customer satisfaction is firstly defined based upon literature and suggestions from the operations management. Then, the model is shaped and refined through a company-wise survey, filled by the sales department and the field engineers, who are the ones involved in the customer satisfaction aspect of sales.

All the remaining tasks involve collecting data from Instron's databases:

- previous years' sales
- product types
- inventory locations
- costs and prices
- replenishment lead times
- manufacturing run times and set-up times
- current reorder points and quantities

The necessary information is collected through IBS. IBS is an Instron database management system that tracks all the information associated with orders and products. For each order placed by customers, IBS contains order number, dates, quoted lead times, standard costs, gross price, discounts and a number of other entries. For each product, IBS contains item number, bill of materials, information about suppliers and planners, current inventory levels and limited inventory level history, lead time and a number of other entries.

IBS is used in all the departments in the company. The sales people, when dealing with customers, use IBS to get the expected lead times, to check what is available in stock, to check prices and costs and to handle orders. The employees working in the factory floor update it when parts arrive from suppliers, when products are shipped, when changes are made to the orders, when WIP inventory is used and a part is assembled and in several other cases. Moreover, all the other employees often use IBS to get required information for analysis purposes or to update it.

In order to collect the needed data, reports are automatically generated by IBS. IBS can be queried with a list of items or orders, and the required information is written on Excel spreadsheets. The result is that every analysis or manipulation which starts from the generated spreadsheets can be easily repeated and updated by using the same type of queries.

4.5 MATLAB implementation and reusability

4.5.1 The need for a tool

The goal of the project at Instron is not only to provide a numerical solution to the problem of which control policy and which parameters should be used. Also, a fundamental goal is to provide a long term solution framework, so that, year after year and quarter after quarter, a new numerical solution can be computed and used. In fact one has to consider that every product has a certain life cycle and that the demand for each of them changes over time. Therefore, it is clear that the "determination of the right mix" is not something that can be determined once. On the contrary, a regular update of the safety stocks levels and inventory control policies parameters is necessary.

For this reason, since the beginning of the project the research team focused on creating a tool that could be used in the research and that then Instron could use in the future to make the calculations and update the policies regularly.

4.5.2 Reusability

The way we see the solution framework is depicted in figure 4-2. On a periodic basis (the choice of the frequency is discussed briefly in the next paragraph) Instron personnel will update the inventory levels. In order to do this, they will export all the relevant past sales data from IBS (the ERP software they are currently using) to an Excel file using a template that we built in IBS. Then, in a similar way, a list containing the lead times, the lot sizes and other information regarding the items will be extracted from IBS. Also, using an Excel file the user will input eventual information about new products being introduced or changes in costs and prices. Finally these XLS files will be put into the same folder as our software tool (an EXE file) and by just running it a solution will be computed.

The output will be an Excel spreadsheet with the suggested reorder quantities Q and reorder level R. This file will also give the opportunity to the user to manually adjust the suggested Q and R will show the impact of such adjustments on the size of the inventory.

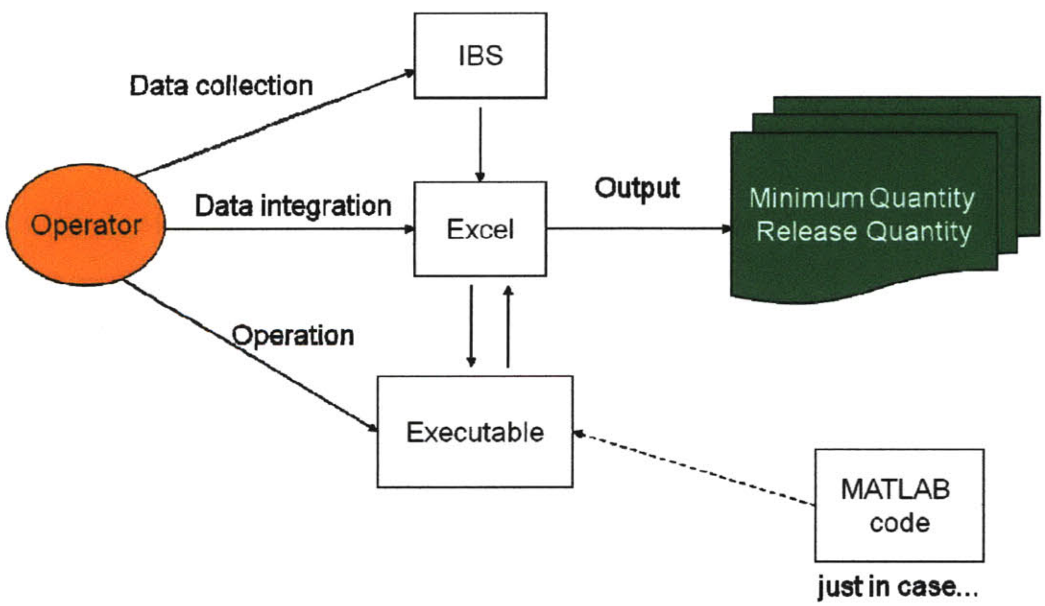

Figure 4-2 - Tool structure and usage

4.5.3 Frequency of stock determination

There is a trade-off in the frequency with which the inventory levels should be re-computed. In fact, on one hand the higher the frequency with which the inventory is re-determined, the best the inventory levels will theoretically perform because they will use the most recent demand information. On the other hand, re-determining the levels involves a certain effort from Instron staff and represents a cost that can balance the advantage of using more recent data. To determine the new levels in fact some data has to be gathered as described above and the computation has to be started. Then the resulting suggested reorder quantities has to be compared with the ones currently in use. If an "R" needs to be updated, then the Kanban card currently used for that item must be reprinted and substituted on the bin.

As seen, a trade-off exists and the correct time does determine new levels depend on the effort necessary to physically update the inventory levels. As a first guess, we think a frequency of 3 or 6 months seems reasonable, unless some of the determining factors (the demand or the lead times for example) will at some point drastically change.

4.5.4 Matlab implementation, reusability and flexibility

The tool described above is built in the Matlab environment and then compiled as an executable file. The choice was suggested by our familiarity with such environment and its power and abundance of mathematical functions. As regards the part of the code which deals with data crunching a C code would have probably been faster but in such a language the optimization part would have been harder to code and, overall, the time required to build the tool and test it would have been much longer. Because in our case the quickness with which the tool was to be built is very important while the computation time required for every run is not particularly significant (as seen the tool is going to be run a few times per year), the choice of Matlab seems to be the best one.

Moreover, Instron owns many Matlab licenses for other reasons so such software is and will be available to the company without any added cost. This is an important issue because, even though we want to give an "easy to use" – "black box" solution, we also want to provide the source code that could be checked and modified in the future and while to run the exe file Matlab is not necessary, to modify the source code is.

5. Demand analysis

The early stage of the project includes the volume and profit analysis of the Instron product line. The main scope of this analysis is: characterizing structure and segmentation of the product line, analyzing the distribution of profit and volume made by Instron over the product line and identifying the eventual hanging fruits. This chapter describes how this analysis was performed and presents its conclusions.

The data used for the demand analysis is collected through the Instron database management system IBS. One of the reports available from IBS is a list of purchase orders (POs) released in a certain period of time (the initial demand analysis described in this chapter refers to the years 2007 and 2008). In the report, associated with each purchase order, the following information is contained:

- Order number
- Type of product (ex. Purchased part, stocked assembly, purchased assembly, etc.)
- *Level* of the order (system order, OTC, warranty replacements, etc.)
- Order *class* (for system orders; model of the machine sold with the order)
- Item number
- Quantity shipped
- Standard cost
- Price (gross, discount, net)
- Order entry date

Using the item number, the products involved in the project are separated from the others, and using the order entry date, the orders of 2007 and 2008 are separated. Using net prices and quantities shipped, volume and profit analysis can be performed

5.1 Product segmentation and Pareto analysis

In a high complexity and variety environment, where the product line contains more than a thousand items with costs ranging from $0.01 to a few thousand dollars, complex and optimal inventory control policies and production scheduling methods could result in waste of time and resources. In the operations management (mainly inventory control and production scheduling) the efforts have to focus on the right, limited set of products.

An effective way to distinguish the most profitable products of a product line is to classify them by profit or by volume. However, if we want to define categories or classes of products, dividing lines have to be set. This is in general a very subjective decision; moreover, the classification should be:

- Flexible; it does not need to be adapted for every small change in the distribution of profits.
- General; it has to be adopted for very different products.
- Simple.

Once the least and the most profitable items are identified, different management policies can be designed for the two categories. Only the most important ones will benefit from the main resources of a company (inventory space, priority in scheduling, replenishment methods).

The *Pareto principle* describes one way to identify such a classification. Applied to profit analysis of a product line, it states that, on average, the 20% of the products make the 80% of the total profit made by all the products in a certain period of time. In this way, the most profitable products can be defined as the 20% that makes the 80% of the profit. The products in the above mentioned 20% are also called *80s* while the remaining products are called *20s*, and the principle is also called "*The 80/20 principle*".

In order for the 80s to be found, the products have to be classified by profits and volume. The profit analysis is only significant if the products are first divided into categories, or segments, such that products in the same segment have similar application and profit per unit. Moreover, the volume analysis requires correct product segmentation; this is because products of very different categories can be sold with completely different quantities. For example, in Instron Electromechanical (EM), a customer can buy a frame with two grips, and each grip has two faces on the contact points; the profitability of frames and faces cannot be compared by comparing their volumes, because four faces are sold every time a frame is sold.

In Instron EM, among the products that have to be considered for this project, the following product segments were identified:

- Grips
- Fixtures
- Faces
- Coupling and adapters
- Compression anvils and anvil sets
- Video extensometers
- Computers
- Other accessories

5.2 Results and conclusions

The product line was analyzed according to the *Pareto principle*, both by profit and by volume. At first the *80s* were identified in each segment. In addition, the profit analysis had an important result in identifying the products that contribute in an insignificant way to the profit made by the segment. These *tail products* (also referred to as *hanging fruits*) were identified as the least profitable items which, all together, make less than 1% of the profit made by that product segment. In a high mix product line, the number of tail products can be significant, because the product line is more difficult to manage.

Drawing from the data of 2007 and 2008, a report is created with all the results of the 80/20 analysis, containing graphs and tables of profit and volume analysis, lists of *80* products and tail products. Table 5-1 shows how this analysis is performed for grips by volume. At first all the orders obtained from the IBS reports are elaborated to calculate the total volume of each grip in 2007 and 2008. Then, the grips are put in a table, sorted by decreasing volume. The table also shows the percentage of total volume made by each grip. Finally, the cumulative percentages are calculated. The 80s are highlighted in green and a double line marks the 80/20 limit, while the tail products are highlighted in dark grey.

Table 5-1 – Percentage of profit of grips in 2007-08 and Pareto analysis

Item #	Description	% of profit	Cumulative
X01	GRIP 1	9.82%	9.82%
X02	GRIP 2	9.40%	19.21%
X03	GRIP 3	9.09%	28.30%
X04	GRIP 4	6.67%	34.98%
X05	GRIP 5	5.62%	40.59%
X06	GRIP 6	5.37%	45.97%
X07	GRIP 7	4.47%	50.44%
X08	GRIP 8	4.33%	54.77%
X09	GRIP 9	4.27%	59.04%
X10	GRIP 10	4.15%	63.19%
X11	GRIP 11	3.55%	66.74%
X12	GRIP 12	3.43%	70.17%
X13	GRIP 13	2.40%	72.58%
X14	GRIP 14	1.97%	74.54%
X15	GRIP 15	1.84%	76.38%
X16	GRIP 16	1.75%	78.14%
X17	GRIP 17	1.70%	79.84%
X18	GRIP 18	1.66%	81.50%

X19	GRIP 19	1.31%	82.81%
……	……	……	……
X56	GRIP 56	0.19%	98.83%
X57	GRIP 57	0.19%	99.01%
X58	GRIP 58	0.13%	99.14%
X59	GRIP 59	0.12%	99.27%
……	……	……	……
X79	GRIP 79	0.00%	100.01%
X80	GRIP 80	-0.01%	100.00%

Figure 5-1 shows a visual example of the results of the 80/20 analysis, contained in the report. All the grips are on the x axis, identified by the item numbers, and sorted by decreasing profitability. On the y axis, there is the percentage of the total profit made by each product in the two years of 2007 and 2008. The red vertical bars show where the 80s and tail products are.

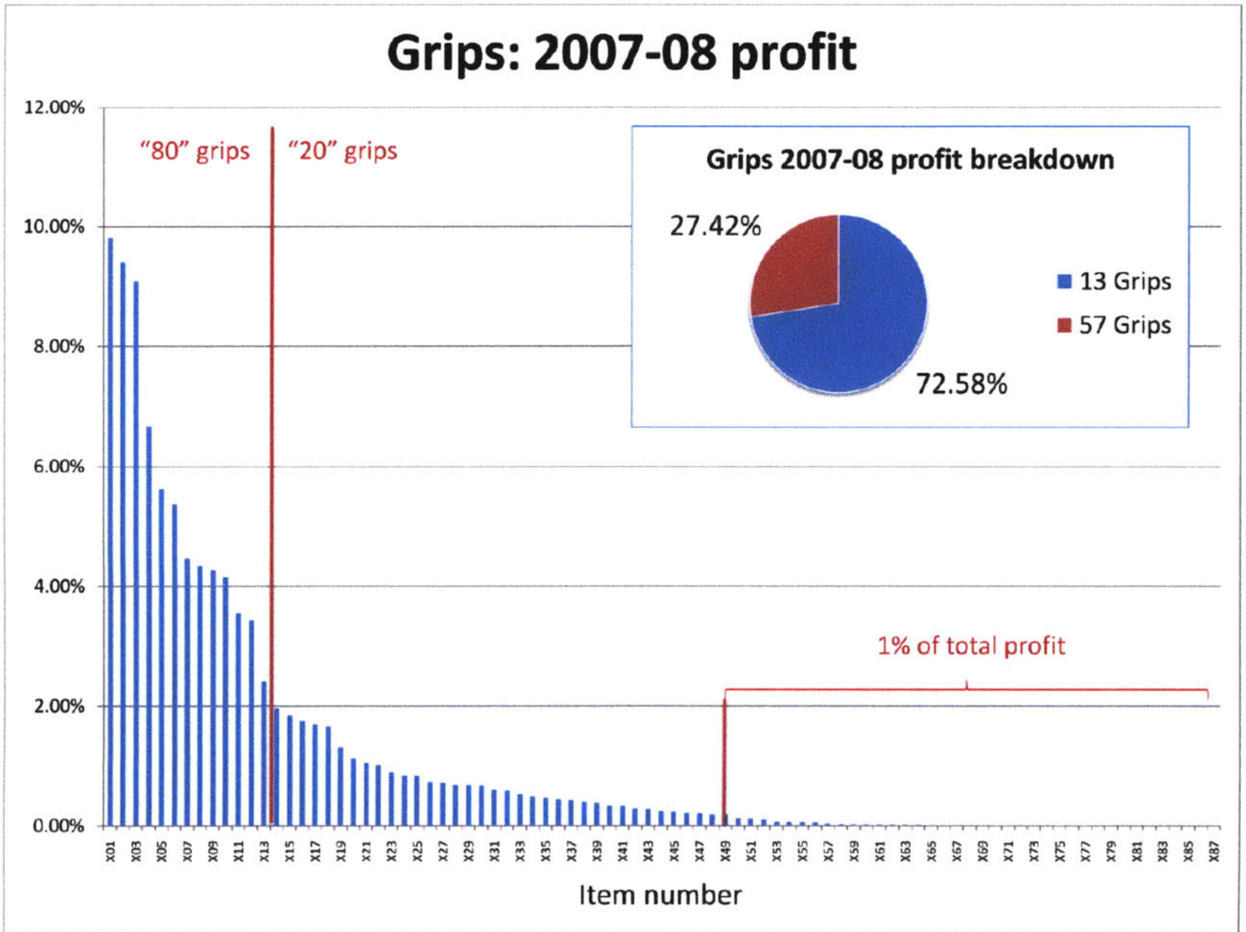

Figure 5-1 - Visual 80/20 analysis

The report containing all the information coming from the Pareto analysis is given to the operations and manufacturing managers. As discussed in this chapter, this report is important in identifying where the efforts should focus in the product line and what products present opportunities of being discontinued or reviewed. However, by only considering the results of this analysis, sometimes the wrong conclusions can be drawn; as discussed in 2.2 and 4.3.2, the correlation analysis has to be considered together with the Pareto analysis, in order to take into consideration the importance of the system orders and of the products being sold together. The correlation analysis and its results are described in a more complete way in [26].

6. Customer defection model

When purchasing a product, the customers in general can have different expectations. They could either expect immediate delivery or be flexible about the shipment date. A customer, in general, is willing to wait up to some maximum waiting time and is likely to cancel the order in case the waiting time is more than that.

The customer expectation needs to be considered in modeling the manufacturing systems, because it determines the effects of not having some products in stock. If a product is not in stock but can be replenished in less than two days, for example, the customer is more likely to accept the quoted waiting time anyways.

This topic is referred to as *customer expectation*. Sometimes the term *customer defection* is also used, because the goal is to understand when the customers will cancel the orders depending on the waiting time.

In this work, the goal is obtaining the optimal inventory replenishment policy. In order to obtain the optimum, a customer defection model is included in order to understand for which products making to stock is more critical than others.

6.1 The model

The optimal inventory policy is obtained by maximizing the expected profit of having the products in stock. The concept of service level is used to describe the percentage of time the orders will be fulfilled directly from stock. Let consider the case, however, in which one particular SKU is not on the shelf. The customer would be noticed that a particular product is not on the shelf and that the total waiting time will be n weeks. Would he still go on with the order? And what if the order request was actually for a system including that product?

Let us summarize the background problem. About 1,000 products are taken into consideration. Some of them are assembled in the factory floor, others are ordered from suppliers. The formers are assembled from raw materials; some of these materials are manufactured from the company, while others are purchased from suppliers. Out of all the mentioned suppliers, some are actually internal supplier (other Instron facilities) that ship in less than a week, while others are overseas external contractors. Moreover, the OTC market requires shorter lead times because of the size of the shipment and of nature of the application (substituting broken or outdated parts of machines), while the system orders are always more flexible in terms of waiting times. Finally, the competitors in the market offer short lead times for some OTC accessories, while there is no other company which can sell competitive systems, inclusive of all the accessories, in short lead times.

Based on this information, the need for a general model of customer defection is clear. Once a model is obtained, it will be taken into consideration in order to obtain the different optimal control policies for parts for which the customers have different expectations.

Let us consider a product i with a particular application and the case in which it is not in stock. Let us consider also that it has a replenishment lead time L. L can be the manufacturing lead time, the assembly time or a quantity on which the supplier agreed. Assuming that L also includes order processing time, if a customer places an order, the sales people will quote him a waiting time L. Some percentage of the customers will cancel the orders because of the waiting time L, while others will still place it. Define w_i as the percentage of customers who will still place the order. It will depend on the lead time L:

$$w_i = Prob(\text{Customer still buys item i} \mid item\ i\ is\ not\ on\ the\ shelf\ and\ has\ a\ lead\ time\ L) = f_i(L)$$

This function is different for every item because of the above mentioned characteristics of the product line. As discussed in 3.4, this function can be described by different mathematical expressions; an important conclusion coming from the literature, however, is that numerical results suggest that there is limited sensitivity to the exact shape of the function. For the purpose of this work, the sigmoid expression is used as in [19]:

$$f_i(L) = \frac{1}{1+e^{\gamma_i(L-\eta_i)}} \tag{6-1}$$

While η identifies the lead time corresponding to a defection of 50%, γ is a measure of the steepness. The two parameters need to be obtained. As discussed in the literature review, obtaining these quantities from the data or in any rigorous way is not feasible due to the following reasons:

- Lack of hard data about lost sales
- Customers have different interests, priorities, concerns
- Other reasons (human behavior, complex products interdependence)

If the parameters are estimated, however, the customer defection model can be then taken into account into the optimization. In fact, another service level can be defined. Let us consider a product *i* and the total percentage of orders that are fulfilled for this product, SL_i:

$$SL_i = \beta + (1-\beta)w_i \qquad (6\text{-}2)$$

Where β is the Type I service level, which is the percentage of time the orders can be fulfilled directly from stock. The expression above can be read as follows: the percentage of orders fulfilled equals to the sum of the orders fulfilled from stock and the orders fulfilled (with some waiting time) even if the product is not in stock.

This *extended* service level can be then used in the optimization to better quantify the number of lost orders for a part not being in stock.

6.2 The survey

As mentioned above, the function $f(L)$ is difficult to quantify due to lack of accurate data. The most accurate estimate we could have is the opinion of all the possible Instron customers, which cannot be obtained without significant effort. However, the company's employees who know most of what customer want and accept are the sales people. They are the ones who quote the waiting times and are there when the customer decides he/she will not place an order and says why.

In this work, a reasonable estimate is obtained through a company-wide survey, referred to as the *Customer expectation survey.* This survey is mainly meant to be compiled by the sales people, who are the one who work on orders with the customers. The survey contains general questions about the products, which were designed in such a way that the compiler will not find too much difficulty in answering and at the same time the results can be easily used to calculate the required parameters. It is composed by a letter to the sales people, a page of instructions, and the questions.

The questions in the survey are divided into eleven sections. The first seven sections contain questions about seven different product categories sold by OTC:

- Section 1: OTC Grips
- Section 2: OTC Fixtures
- Section 3: OTC Faces
- Section 4: OTC Coupling and adaptors
- Section 5: OTC Compression anvils and anvil sets
- Section 6: OTC Chambers
- Section 7: OTC other accessories

Sections eight to ten contain questions about the system orders, divided by series:

- Section 8: 3300 systems
- Section 9: 5500 systems
- Section 10: 5800 systems

The last section contains additional questions, meant to extract additional useful information about dealing with customers and about lost orders, which are not described in detail in this work.

- Section 11: Additional questions

In order to better understand how the questions are designed, let us consider an example. Figure 6-1 shows an example of simple defection function, with the only purpose of showing how the questions are designed. In this example, the parameters used are $(\gamma, \eta) = (1,7)$.

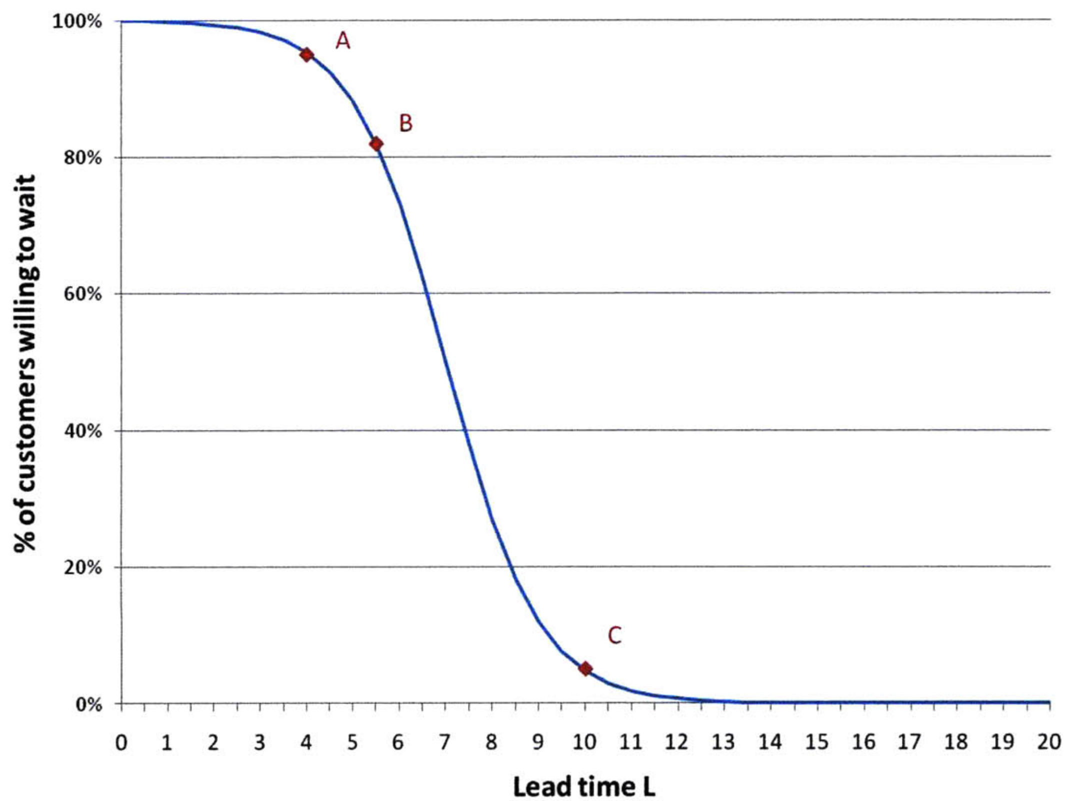

Figure 6-1 - Example of customer defection model

The survey is designed with simple general questions that try to shape the function through finding the three points A, B and C in the graph above. The A point represents the maximum lead time that every almost every customer accepts (95% of them); the B point is the lead time that about 80% of the customers accept; the C point is approximately the maximum waiting time that customer accept: less than 5% of them accept more than that. The three set points of 5%, 80% and 95% are chosen in order to obtain good estimates of the above mentioned three lead times; however, a sensitivity analysis is performed, showing that they are not critical for the optimal control policy obtained.

Through the survey questions, ten different functions $f_i(L)$ can be obtained. Every function describes the customer behavior for a different type of product and order (e.g. grips or fixtures, OTC or systems). The surveyed is given the option of stating that there is no significant difference between one product category and the others.

Example of actual survey questions for grips can be found in Appendix A. In order to find point A, for example, question 1 asks "If the grip is not in stock, what is the maximum waiting time that 100% of the customers will accept?"; similarly, questions 2 and 3 try to address the problem of finding the points B and C. Finally, questions D, E and F help in understanding how valid are the supplied answers for the product category considered. Question E, in particular, asks a level of confidence, which can be used to weigh the answers given.

The next paragraph describes in detail how the results of the survey are used to shape the functions and what are the conclusions once the functions are identified.

6.3 Results

In mathematical terms, the result of the survey is a set of estimates of the lead times corresponding to the points A, B and C. These values are to be used to estimate the parameters of the defection function.

At first, considering each of the three questions, an average of the supplied lead times is calculated, where each answer is weighed using the confidence level. In this way, three values for the points A, B and C are available. Then, being the number of parameters less than the available constraints, the two parameters are obtained through minimizing the sum of the squared errors. In this way, 10 different functions are obtained.

In the described algorithm shaping the defection functions, a particular has to be noted: because of the use of squared errors, the lead times supplied by the survey do not necessarily correspond to the set points of 5%, 80% and 95% anymore. This grade of flexibility, acceptable because of the approximate nature of the answer, makes the choice of the set points A, B and C not critical any more.

The following table shows the average lead times and the defection parameters calculated.

Table 6-1 - Shaping of the defection function based on the survey

	average of lead times from the survey (weeks)			defection parameters	
	95%	80%	5%	gamma	eta
OTC GRIPS	0.65	3.14	6.94	1.097	4.361
OTC FACES	0.63	2.89	6.26	1.236	3.981
OTC FIXTURES	0.65	3.14	6.94	1.097	4.361
OTC C&A	0.62	2.80	5.74	1.420	3.756
OTC ANVILS	0.58	2.80	5.57	1.514	3.699
OTC ACCs	0.58	2.80	5.57	1.514	3.699
OTC CHAMB	4.09	7.80	12.51	0.889	9.330
3300	3.26	5.44	11.06	0.764	7.243
5500	3.71	6.09	12.00	0.722	7.987
5800	4.06	6.50	12.74	0.687	8.501

In order to interpret the results, let us consider the graph of the defection functions for four significant product categories: OTC grips, OTC chambers, 3300 systems and 5800 systems. The other OTC accessories have curves similar to the OTC grips, while the 5500 systems are in the middle between 3300 and 5800 systems. The four significant functions are shown in the following figure.

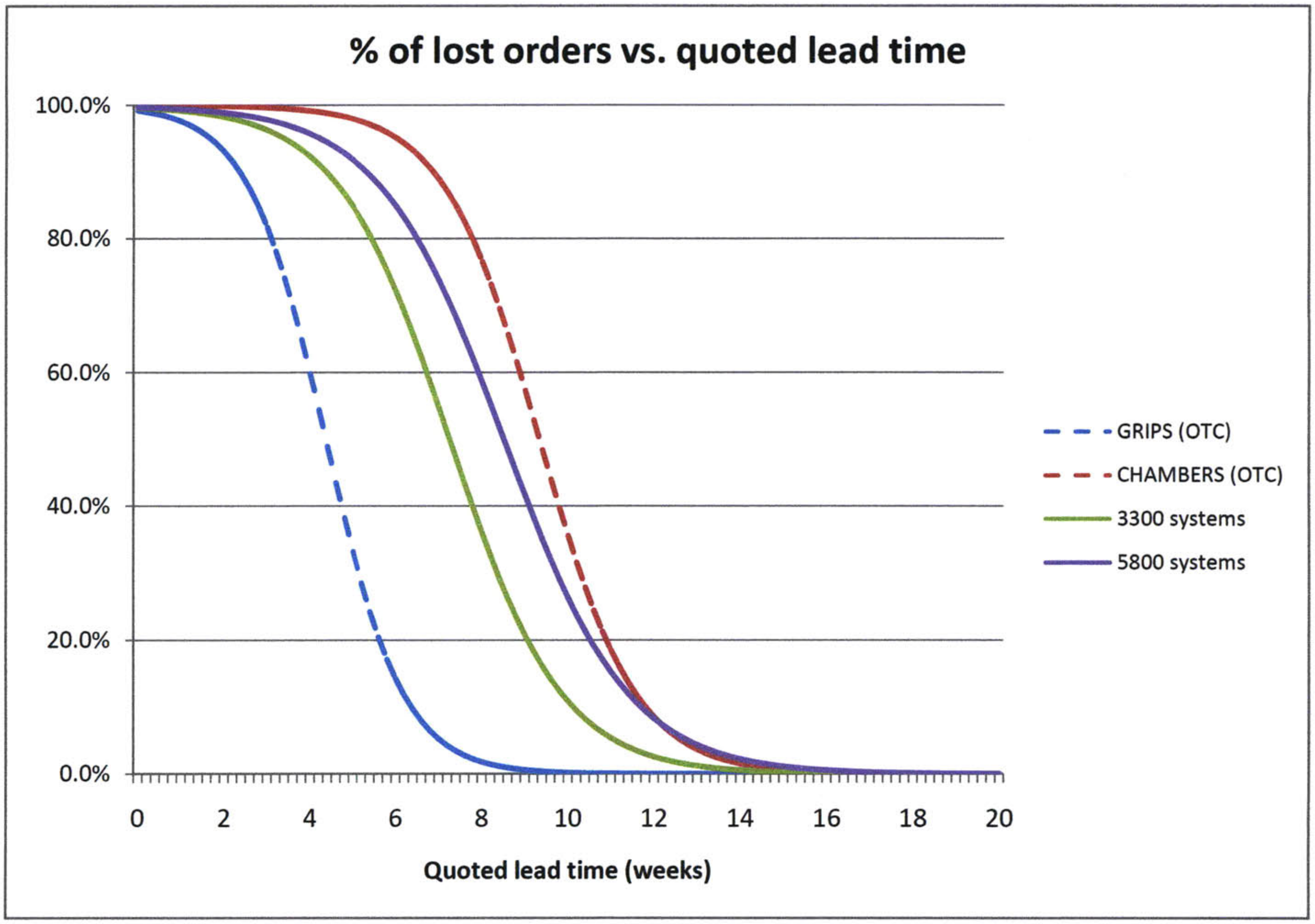

Figure 6-2 - Defection function results for four significant product categories

The graphs show that a lead time of less than two weeks for grips is necessary for the company not to lose a significant quantity of orders for grips not on the shelf, while more flexibility is allowed for systems and chambers. In addition, if the grips have lead time values of more than six weeks, most likely the orders will be lost if the grips are not on the shelf.

As already discussed, the systems allow more flexibility for different reasons. Firstly, they are shipped when a number of different accessories plus the frames are ready; this means that the customer the total waiting time is less sensible to the one of a single accessory. Secondly, customers usually plan capital expenditures some time in advance or even defer the shipment by their own decision because of capital availability issues. Thirdly, if a customer desires a particular system with a particular set of accessories in it, finding the simple alternative in the market is not easy. In fact, competitors would not have the same set of accessories, or the customer would have to buy machine and accessories separately. Finally, the chambers are very low to build and customize, thus being shipped with longer lead times in general.

Another important result is deduced as follows. If the company manages to reduce the replenishment cycle of grips to less than two weeks, the defection function would say that there is opportunity of having zero inventories. In fact, according to the results, customers are willing to wait such a lead time for their orders without canceling them. However, there are at least a couple of reasons why this is not easy. For example, holding no inventory would require adding manufacturing capacity to the floor; in fact, when one week sees a significant number of orders at the same time, those grips have to be built immediately, and this requires assembly people. Moreover, even if the assembly people are enough and work quickly enough, the raw materials have to be in stock or they have to be replenished quickly enough. The inventory control of raw materials is discussed in the following chapter.

7. Raw materials inventory

7.1 Supporting the FG inventory

As discussed in 4.3.5 and 4.3.6, the main goal of the project is designing the optimal inventory control policies at the FG level for several different categories of items. The optimal inventory control policy is the one which optimizes the profit, and is designed by choosing the right values for Q and R in the QR policy. The design of these policies is introduced in chapter 4 and the different topics (demand analysis, customer satisfaction, optimization, correlation and simulation) are explained into detail by this thesis, [26], [27] and [28].

Some of the accessories and products that have been considered are purchased items; for these accessories, the only inventory is held at the FG level. Some other parts, mainly grips, are assembled in the factory floor and require two different levels of inventory: finished goods (assembled grips) and raw materials (here also referred to as *RM* or *parts level*). For every single grip, the bill of materials is available through IBS. Given that the grips are assembled at once from the raw materials, and no intermediate level inventory is held in the factory, the Work In Progress (WIP) inventory does not need to be considered. Figure 7-1 shows an example of such inventory levels.

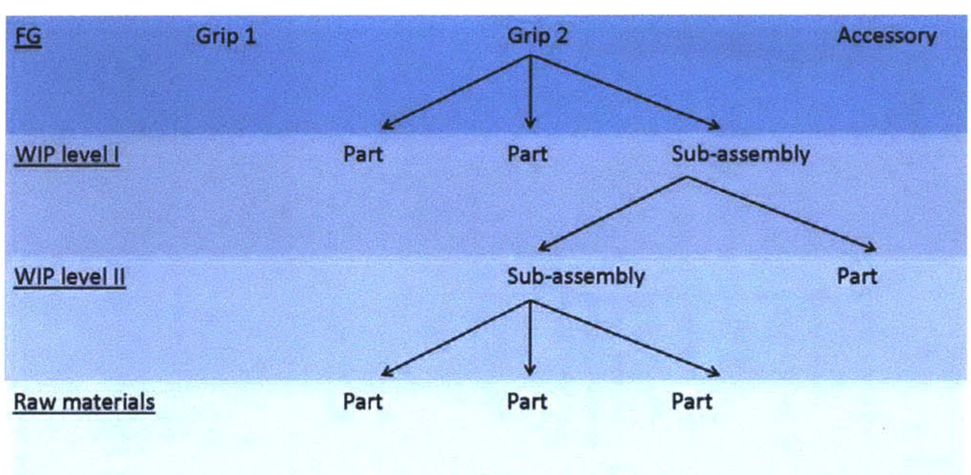

Figure 7-1 - Inventory levels in the grip assembly. Note that no WIP inventory is actually held on the floor.

In designing and optimizing the finished goods inventory control, the assumption that all the raw materials are always available is made. Here we discuss how to manage the raw materials inventory levels in order to make sure that the results of the optimization are still valid.

Moreover, the current inventory control policy at the RM level is only based on financial considerations, calculating the total amount spent on each different part by the company in a year. The limits of the current control policy are discussed and a comparison of the results is made.

7.2 Designing the inventory control policy

Considering the availability of the Instron "Kanban cards", the reorder point policy (QR) is considered the perfect fit for the raw materials inventory. In fact, it is immediately applied without any change and / or training. In addition, the training needed is reduced, given that the same policy that is finally recommended for the FG inventory level.

The QR policy at the parts level is designed and implemented as follows. Two quantities define the policy: the reorder point (R) and the reorder quantity (Q). Figure 7-2 shows how the policy works. The curve shows the inventory level (in units) versus time. The basic rule is that a quantity of Q units is ordered when the inventory level drops to or below R. The Q units will arrive and replenish the inventory only after the replenishment lead time (L). In this chapter, the assumption that the demand is a normal random variable is made. The distribution is described by the average μ and standard deviation σ.

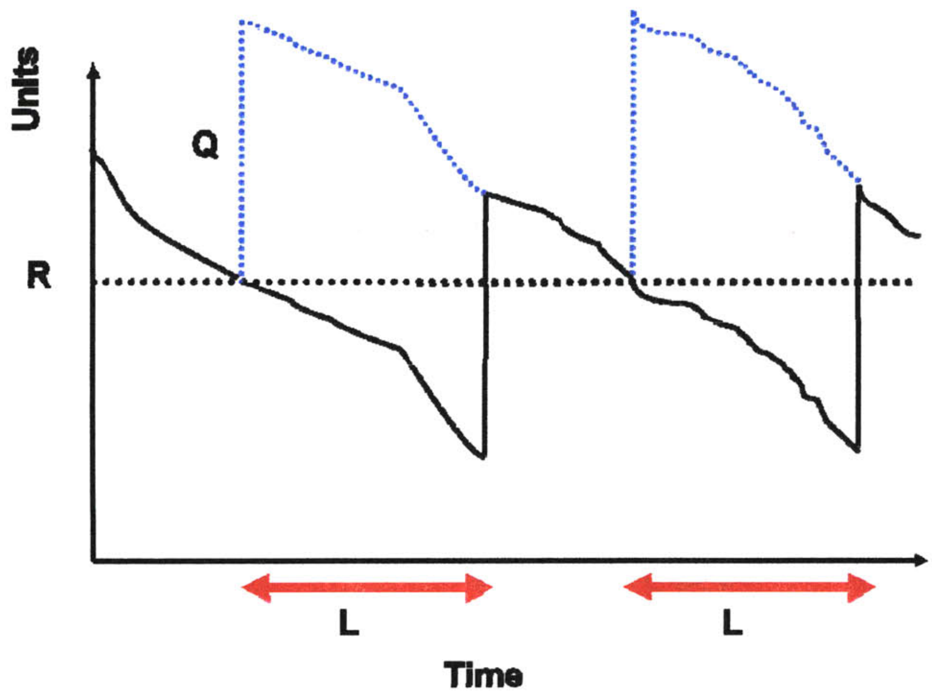

Figure 7-2 – Inventory level vs. time in the QR policy

7.2.1 Determining R

Setting the reorder level determines the probability of having stock out. It is set so that the demand over the lead time L will cause stock out only with a very small probability. Considering average and standard deviation of the demand, this is obtained as follows:

$$R = \mu L + z_R \sigma \sqrt{L} \tag{7-1}$$

Where z, in the normal distribution, is also called *safety factor*. The probability of having stock out is determined through choosing z. If $z = 3$, for example, according to the cumulative normal distribution, the probability of having stock out is about 0.135%.

In order to make sure that the FG inventory levels are still close to the optimum, the safety factor has to be "high enough". At the same point, having z too high would make the inventory levels higher than necessary. There is not any standard limit for the safety factor, but the right value can be chosen through sensitivity analysis. In this case, z is chosen to be equal to 2, in order to make the probability of having stock out slightly more than 2%.

$$R = \mu L + 2\sigma\sqrt{L} \tag{7-2}$$

The determination of μ and σ in the part level is described in 7.3.

7.2.2 Determining Q

In general, the reorder quantity is set according to external constraints or to the economic order quantity (EOQ). In addition to these two considerations, Q has to satisfy two constraints:

- It has to be more than the average demand over lead time, in order not to drop below R before the replenishment quantity arrives;
- It has to correspond to an acceptable reorder frequency. Depending on the agreement with the suppliers, in fact, if Q is too low the reorder frequency is too high.

In this case, the EOQ model cannot be used in this case, because there are no fixed shipping and setup costs, and the inventory holding costs are not quantified with a per unit quantity without significant approximations or difficulties.

The demand over lead time is described by:

$$Q \geq \mu L \tag{7-3}$$

However, by using this constraint, the reorder quantity will cover the demand over lead time only on average. Another option is adding a safety factor also in the reorder quantity:

$$Q \geq \mu L + z_Q\sigma\sqrt{L} \tag{7-4}$$

The safety factor can be also chosen in order to make sure that the inventory will be always replenished to more than the reorder level R. In order to do this, it has to be:

$$z_Q > z_R \tag{7-5}$$

The external constraints are the lot sizes in the replenishment of these quantities, agreed with the suppliers. For the part level, it turns out that there are no significant constraints: the purchasing department usually comes to agreement with the suppliers for the quantities to be ordered.

In conclusion, the determination of the reorder quantities has to satisfy a few constraints depending on the demand and the reorder frequency. The proposed solution is only based on the demand, and the feasibility of the reorder frequency is postponed to the implementation and validation phase, to be made with the purchasers.

In particular, two different expressions are proposed depending on the reorder frequency:

- The reorder quantity equals to the reorder level plus an extra safety factor:

$$Q = \mu L + (z_R + 1)\sigma\sqrt{L} \tag{7-6}$$

- Reorder quantity equals 1.5 times reorder level in case the solution above causes the reorder frequency to be too high:

$$Q = 1.5R \tag{7-7}$$

7.3 Statistics of the part level demand

As regards the mean and standard deviation of demand for raw materials, two ways of obtaining them are described.

By considering that average and standard deviation of demand for finished goods, an estimate of the demand for parts can be easily obtained. Let us consider grips G_A and G_B both, which have demand X_A and X_B described by (μ_{GA}, σ_{GA}) and$(\mu_{GB}\ \sigma_{GB})$, and need the body B_A (among other parts), in quantity 2 per grip, to be assembled; moreover, no other grip needs the body B_A. The demand for body A in a quarter is described by:

$$X_{BA} = 2 * X_{GA} + 2 * X_{GB} \tag{7-8}$$

Thus, the average demand of body BA will be:

$$\mu_{BA} = 2\mu_{GA} + 2\mu_{GB} \tag{7-9}$$

Moreover, under the assumption that the demand of grip A and B are independent, we can also say:

$$\sigma^2{}_{BA} = 4\sigma^2{}_{GA} + 4\sigma^2{}_{GB} \tag{7-10}$$

Drawing the conclusions, if the assumption of independent demand is reasonable, an easy way of calculating average and standard deviation of demand of parts is available. The problem with this solution is that it over estimates the variance of the demand, thus increasing the levels of inventory.

Another more direct way of describing the statistics of parts demand takes advantage of the existing grade of correlation in the FG demand. By considering the grip orders, one by one, every grip order can be split into the different orders for the different parts needed, by using the bill of materials for that grip. This will translate the list of grip orders into a list of parts orders, from which average and standard deviation can be obtained. This method requires generating code which goes through the list of orders, and calculates the actual distribution of demand for lower level parts. This second method gives better results but requires more work.

In conclusion, the second method is used. The MATLAB code can be found in Appendix B.

7.4 Replenishment lead times

In general, Instron tracks the inventory levels and the replenishment lead times through IBS. The replenishment lead times come from the agreement with the suppliers. Unfortunately, only a small portion of the actual values is available on IBS, because they are not recorder on a regular basis. For most of them, only false standard values are available.

Given that the QR policy is widely based on the replenishment lead time for its implementation, data accuracy issues are significant in its design. Thus, only parametric values for Q and R can be proposed if these values are not available.

In order to propose valid values for R and Q, two strategies are undertaken in order to give final recommendations:

- Through a meeting with the supply chain managers, as many information regarding lead times as possible is obtained. For some parts, standard obtainable lead times are available, which depend on the value of the part (defined as volume times cost per unit). For others, temporary reasonable values are used.

- A parametric form of the inventory control policies is prepared. It consists in an Excel spreadsheet, where the user can insert lead times and other information in order to obtain all the values of Q and R. The spreadsheet also gives the possibility of studying the sensitivity of inventory levels to the choice of Q and R.

As a general consideration, the final recommendations will underline the importance of recording the information about lead times in a lean manufacturing environment. The provided tools (in this case the spreadsheet) can be used as a design tool in understanding the results obtainable depending on the different agreements with the suppliers.

7.5 Current policy

The current inventory control policy is based on financial considerations rather than statistics of demand or replenishment lead times.

At first, the parts are divided into four different categories depending on their different financial value to the company. The value of each part is obtained as yearly average demand times manufacturing cost per unit. The four different categories (A to D) are shown in the table 7-1. The third column contains the range of values corresponding to each class. The D class also has a constraint in terms of cost per unit.

Table 7-1 - Definition of the four value categories

Grade	Cost per unit (c)	Total value per year (v)
A	$0-inf	$5,000<v<inf
B	$0-inf	$1,000<v<$5,000
C	$0-inf	$500<v<$1,000
D	c<$5	v<$500

Table 7-2 shows how the inventory control policy is designed according to the division in classes. The system used is based on the same basic rule of QR (order the reorder quantity when the inventory is at or below the reorder level), but the values are not obtained through statistical considerations.

Table 7-2 - Current reorder policy

Grade	Reorder level (months)	Reorder quantity (months)
A	0.5	1.0
B	2.0	3.0
C	3.0	6.0
D	3.0	12.0

The reorder quantity and reorder level only depend on the financial value of the part. Moreover, once the classes are obtained, the values of R and Q are not based on any rational consideration based on the class, but on accepted rules of thumb. One of the main reasons why this policy is used is that the only hard constraint that the company has is that the inventory levels have to be below two months on hand all the time. Thus, no other performance measure is immediately considered other than this constraint.

The range of replenishment lead times that the suppliers will provide also on the class of the part. For example, the suppliers are expected to keep all the A parts in stock, thus providing lead times everywhere below one month. The reorder methods, then, are based on very conservative estimates of the lead times, that is the same for all the parts in one class. What actually happens, however, is that some suppliers will be able to ship in a few days, while some use to ship overnight. A first, more realistic estimate of these lead times is obtained talking with the purchasers and shown in table 7-3. For simplicity, the values are the same in every class. These values are used in 8.1 to discuss the results of the proposed policy.

Table 7-3 - First estimate of average current lead times vs. part grade

Grade	Lead time (days)
A	7
B	15
C	30
D	60

Given that lead times and demand variability are not taken into consideration, two important consequences have to be considered.

Firstly, given that the policy does not consider the lead times, both the possibility of having frequent stock out and of having too high inventories are ignored. If the replenishment lead times for some parts are too long, and the part is A or B, the possibility of having stock out is significant. Moreover, if the part can be very easily replenished from other Instron facilities in two days, having high reorder levels (C or D parts) is not necessary.

Secondly, let us consider two parts, the first being used regularly to assembly four or five grips with regular demand and low volume, the second being used only to assemble one or two grips that have irregular demand and higher volume. According to the current policy, the two parts could have the same reorder levels, having similar financial values. However, it is clear that the part with higher variability needs more inventory than the one with regular demand. Thus, the probability of stock out is irregularly distributed among the parts: some parts will always be on the shelf while some will be out more frequently.

7.6 Comparison of the two policies

In this paragraph the results obtainable with the QR policy are shown by a comparison with the current policy. For the QR policy, the parametric version is used; the results are shown depending on the values of the lead times for all the parts. In this way, the importance of the above mentioned Excel spreadsheet as a design tool is demonstrated.

For the QR policy, Q is determined in the first of the two ways described in 7.2.2:

$$Q = \mu L + (z_R + 1)\sigma\sqrt{L} \qquad (7\text{-}11)$$

7.6.1 Inventory value on hand

Figure 7-3 shows the average inventory value on hand obtained with the current policy and with the QR policy depending on the replenishment lead times that the parts have. The graphs are obtained through one approximation: the lead time is the same for all the parts. Even though this approximation is not valid in general, it is very effective in showing the differences between the two policies versus the lead time.

The average inventory value on hand for the two policies is calculated as follows:

$$\overline{VOH} = c * E[I] = c * \left(R + \frac{Q}{2} - \mu L\right) \qquad (7\text{-}12)$$

Where c is the cost per unit and μL is the demand over lead time.

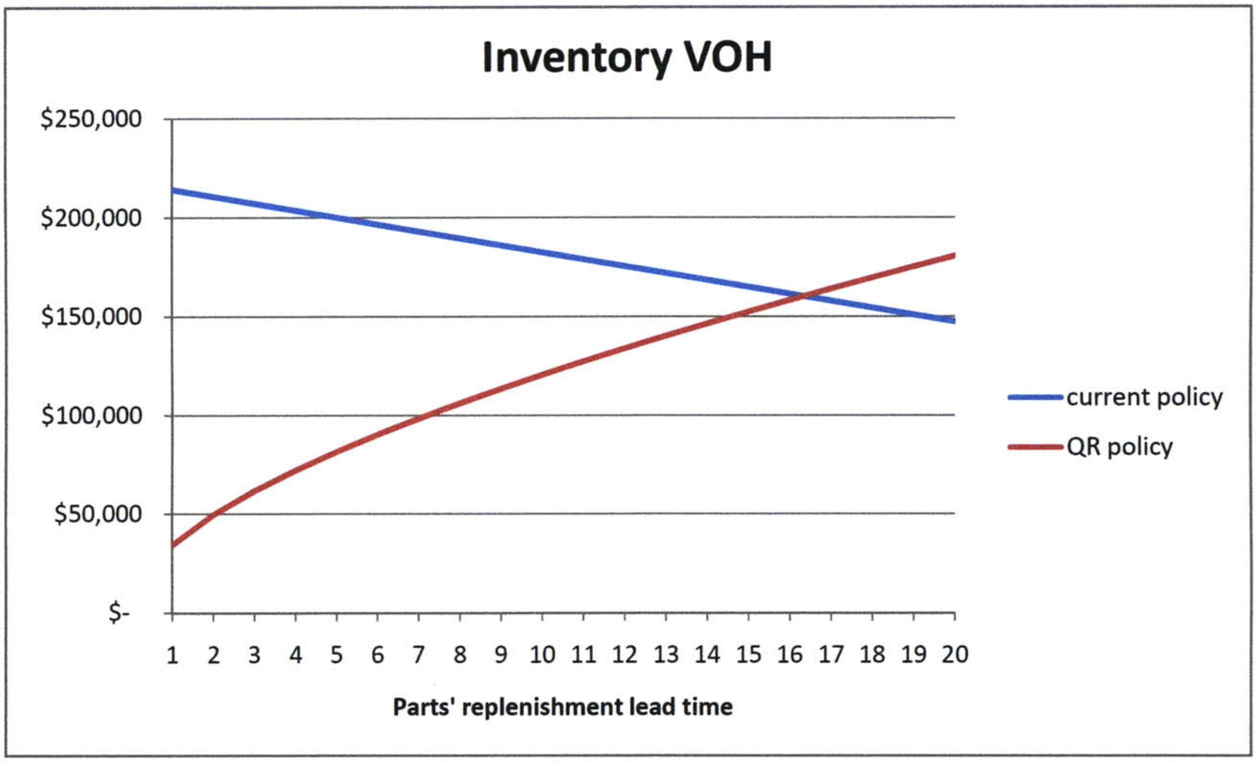

Figure 7-3 - Average inventory value on hand comparison

With the current policy, the inventory VOH decreases linearly when the lead time increases. This is because reorder level and quantity are fixed while the amount of inventory consumed during the lead time increases linearly. The fixed quantities are such that the inventory levels do not change by a relatively significant way with changing lead times.

The QR policy, on the other hand, considers the lead time values in the calculations. If the lead time is low, the inventory VOH is very low, because high levels of inventory are not necessary. If the lead time increases, in order to ensure low stock out probabilities (thus high service levels), the inventory levels are higher.

Comparing the two policies, it is apparent that with lead times shorter than two weeks the QR policy decreases the inventory VOH by a significant amount, ranging from -84% to -13%. Moreover, even when the VOH is similar to the current policy, the R and Q are designed depending on lead time and variability; thus, we should expect significant differences in service levels.

7.6.2 Service levels

Figure 7-4 shows the average service levels obtained with the current policy and with the QR policy depending on the replenishment lead times that the parts have. The same approximation made in 7.6.1 for the lead times is used. For the QR policy, the service level is fixed and depends on the choice of the safety factor z, which was set to 2. For the current policy, based on the assumption that the demand is normally distributed, the service level is calculated as one minus the average probability of having stock out using the proposed reorder level and quantity.

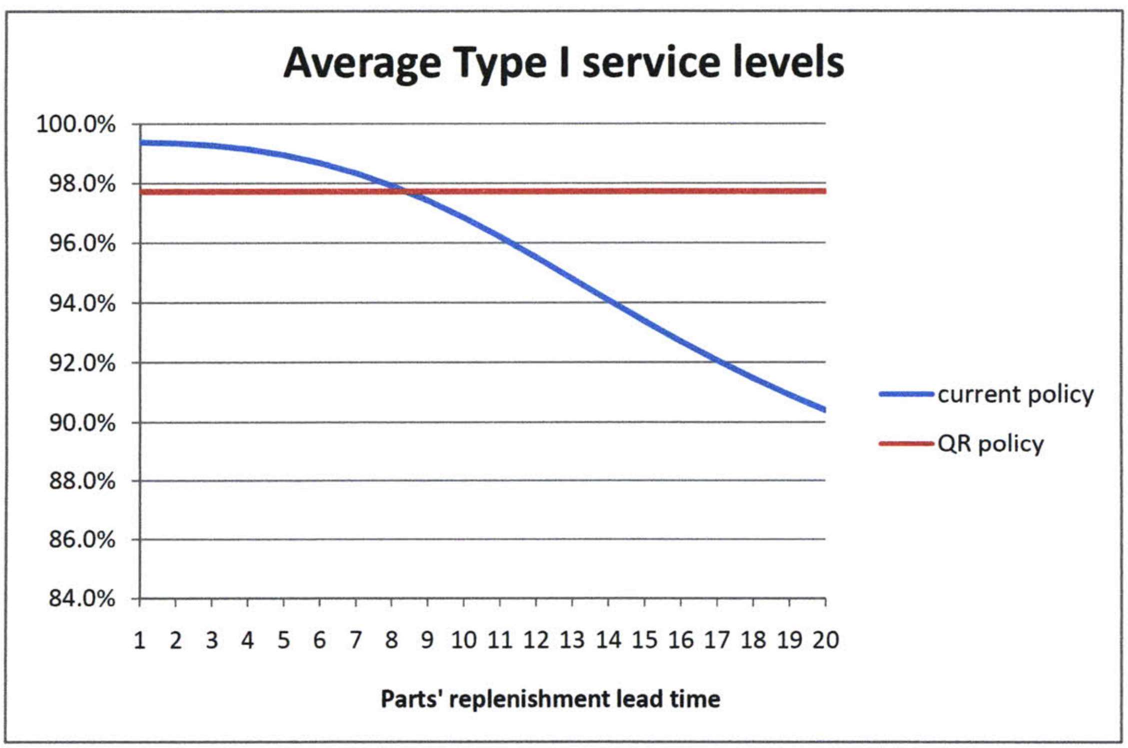

Figure 7-4 - Service level vs. lead times

With the current policy, the average service level decreases as the lead time increases as well. With the increasing lead time, the probability of having stock out increases because the increase service time is ignored in designing the control policy. Being the reorder levels fixed, in fact, if the lead time increases, it is more likely that the inventory level drops to zero before the replenishment takes place.

From this graph, it is clear that even with longer lead times, where the inventory VOH is comparable, the service levels are much better with the QR policy. Moreover, another important consideration has to be made. The service levels are calculated for the individual parts, not considering that more than one part is necessary for the grips to be assembled. Thus, if the probabilities of having stock out for the single parts are high, the probability of not being able to assemble the grips is even higher. For example, if one grip needs three parts, and the stock out events for the three parts are independent and have probabilities of p, the probability of not being able to assemble the grip is p^3.

8. Results and discussion

8.1 Raw materials inventory

As introduced in chapter 4 and further described in chapter 7, purpose of the project was also to provide a raw materials inventory control policy supporting the finished goods inventory. The current policy is value-based: the parts are classified by financial value to the company (classes A, B, C and D) and the reorder quantities and levels only depend on the class. A QR policy with fixed service levels is proposed; the results are here summarized and discussed.

8.1.1 Results

In order to implement the QR policy for the raw materials inventory, some information is necessary. In particular, knowing the replenishment lead times negotiated with the supplier is fundamental. In this paragraph, the results of the QR policy are presented by comparison with the current value-based control policy. Firstly, the importance of the lead time is shown through a parametric comparison; then, the two policies are evaluated with the best current estimate of the lead times.

Figure 8-1 shows the difference that could be made by having more accurate information about the lead times. The graph on the top shows the expected inventory value on hand, while the graph below shows the average service levels. For the sole purpose of showing the differences as the lead times vary, the graphs are based on the assumption that the lead time is the same, and constant, for all the parts. The blue lines represent the current value-based policy, which does not consider lead times or the demand variability. The red lines correspond to the QR policy, implemented using also the lead times and variability information. Two examples are highlighted with vertical lines: a lead time of 4 days and a lead time of 18 days.

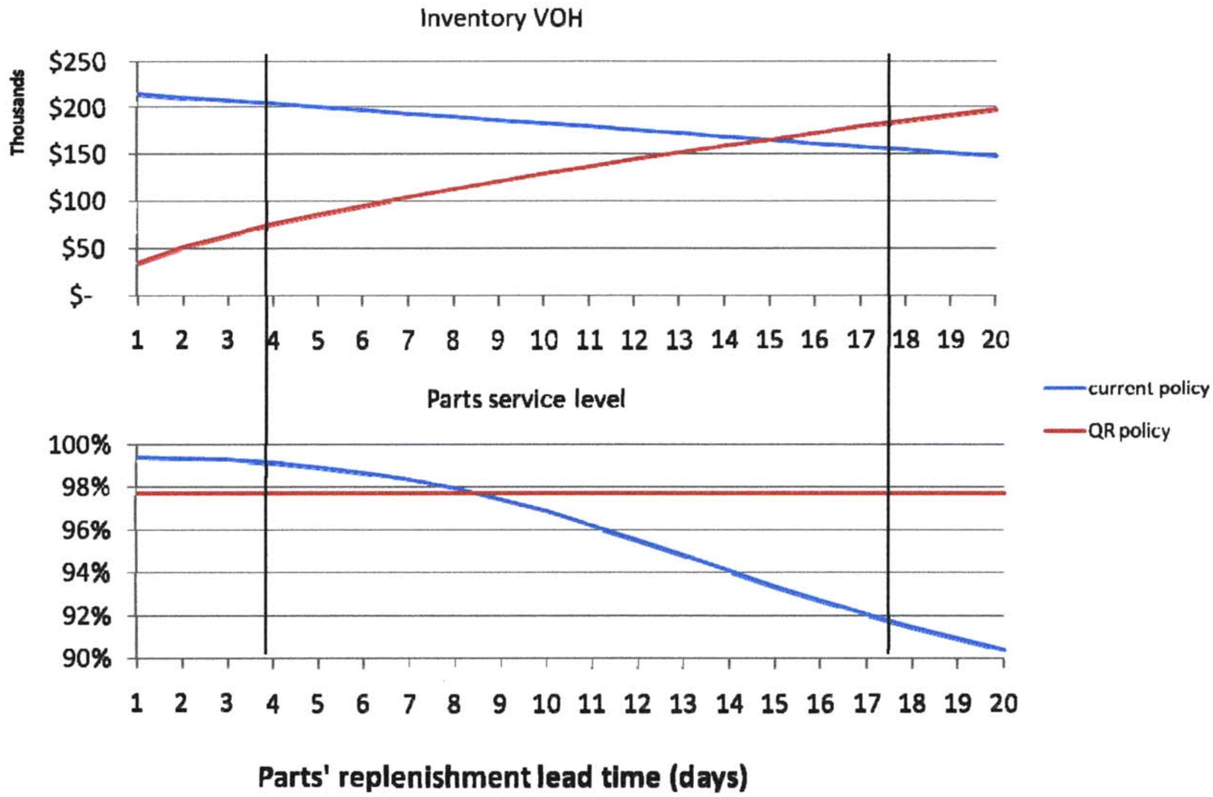

Figure 8-1 - Service level and Inventory VOH vs. lead time

If the suppliers ship more quickly than expected, and the lead time is shorter, both policies have high service levels because the shelves are replenished quickly. Being designed upon the shorter lead times, however, the QR policy manages to accomplish high service levels with low inventories. In the first example, indeed, the value on hand is reduced by three times.

On the other hand, if the lead times are longer, the only way to achieve high service levels is to have higher inventories. Thus, the proposed policy suggests inventory levels that are comparable or even higher than the current ones. The QR policy, on one hand, uses the information about lead times in order to maintain high service levels; the current policy, on the contrary, does not consider them, causing a significant percentage of lost orders (orders meaning grips to be assembled), as shown in the second example.

An estimate of the actual supplier replenishment lead times is obtained by talking with the purchasing department and described in chapter 7.5. In this case, the lead times are different for each part. Table 8-1 shows a comparison of the results obtainable with the two policies based on this estimate. Moreover it provides an estimate of the savings that would be achieved by agreeing on shorter lead times with the suppliers.

Table 8-1 - Comparison of raw materials inventory control policies

Method	**Average inventory VOH**	**Parts service level**
ABCD - Division by value	$179,731	93.2%
QR – Knowing and using the lead times	$126,299 (-30%)	97.7%

As table 8-1 shows, only as a result of improving the accuracy of lead times, the QR policy would allow achieving high service levels at the same time cutting the costs by 30%. If, in addition, the purchasers obtain agreements for shorter lead times for the most valuable parts, the costs would further decrease.

8.1.2 Discussion

Based on the analysis proposed in chapter 7 and on the results here described, the current inventory policy, which is value-based and does not consider lead time and demand variability, can result in irregular inventory distribution, lower service levels and higher inventory value on hand. A simple QR policy is proposed, which gives better and more regular results.

In designing and optimizing the finished goods inventory control, the assumption that all the raw materials are always available is made. The designed QR policy achieves service levels of about 98% for each part. Thus, the above mentioned assumption can be still considered valid.

However, in order to implement the QR policy, the replenishment lead times are necessary. As a general consideration, the lead times are necessary to make sure that the service levels are high without wasting inventory. Thus, the lead times of every part should be tracked in the way described in section 7.1, and accurate information should be kept on the company databases. In addition, if the suppliers are flexible on the lead times, the Excel spreadsheets can be used in the decision process to determine the correct tradeoff between lead times and inventory value on hand.

8.2 Finished goods inventory

The policy proposed shows potential for a significant improvement in inventory control. Figure 8-2 shows a comparison between the proposed policy, a simple QR policy and the values of Q and R currently in use. Note that the term "simple QR" refers to a QR policy with an equal safety factor z for all the products. The figure shows the expected lost sales, due to products unavailability, versus the total expected inventory held. The amount of inventory held is measured in months on hand (MOH):

$$E[I]_{MOH} = \frac{\text{expected inventory value on hand}}{\text{average monthly demand}} = \frac{\sum_i c_i E[I_i]}{\sum_i c_i \mu_i} \qquad (8\text{-}1)$$

Where c_i is the unit cost of part i, $E[I_i]$ is its expected inventory level and μ_i is its average monthly demand.

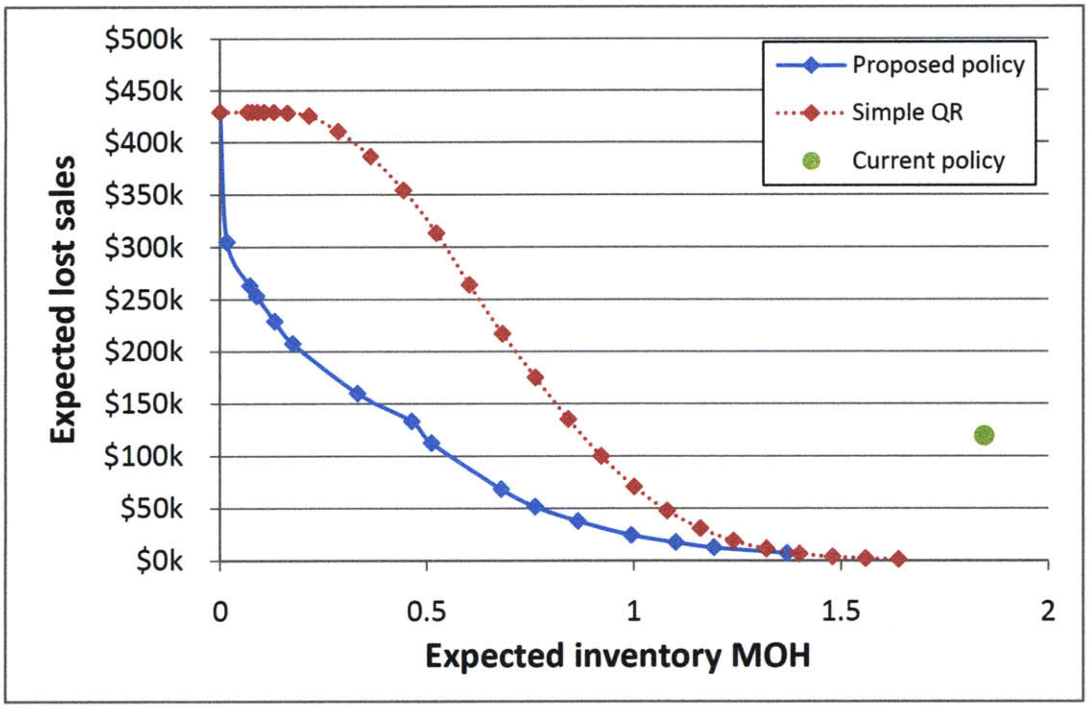

Figure 8-2 – Expected lost sales vs. Inventory MOH

As figure 8-2 shows, the proposed policy outperforms both the simple QR and the current policy. In particular, at the same level of expected loss sales given by the current policy, the proposed policy allows reducing the inventory from about 1.8 MOH to 0.5 MOH. From another point of view, with the amount of inventory currently held, the proposed policy would allow reducing the expected lost sales from about $120,000 per year to nearly zero.

In addition, Figure 8-2 shows that the proposed policy outperforms the simple QR policy. As one might expect, the difference increases as the size of the inventory gets smaller, while it decreases as larger inventory is considered. As a limit case, the value of lost sales achieved by the simple QR with 0.15 MOH is the same that would be obtained by a complete make to order (MTO) policy. With the proposed policy, instead, 0.15 MOH of inventory can halve the expected loss as compared to an MTO policy.

Figure 8-3 shows the expected lost sales value versus the value of the inventory on hand. As one can see from the graph, if a solution with 1.2 MOH is chosen (the penultimate point on the purple line) the inventory could be reduced from \$240,000 to \$157,000.

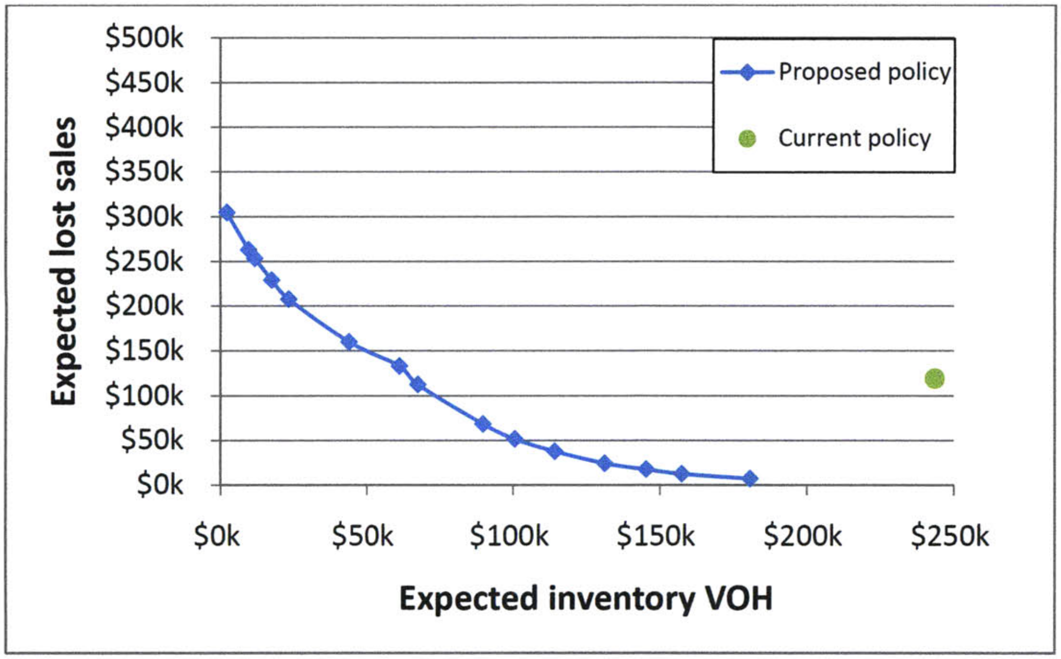

Figure 8-3 - Expected lost sales vs. Inventory VOH

Considering the trade-off between size of inventory and expected loss sales, a good compromise is a solution with an expected inventory of 1.2 MOH. This allows both reducing the amount of inventory and the expected loss sales. Moreover, a preliminary analysis of the maximum inventory levels shows that, with this solution, it is unlikely that the inventory levels measured at the end of one month will go above 2 MOH (considering the monthly demand variability). Table 8-2 shows a comparison between the proposed solution (with 1.2 MOH) and the current policy.

Table 8-2 - Current policy vs. 1.2 MOH solution

	Current Policy	Proposed Policy
Average value of Lost orders	$119,391	$12,453
Expected Inventory (MOH)	1.85	1.19
Expected Inventory (VOH)	$243,481	$157,411

8.3 Simulation

The aim of simulation is to validate the results of the optimization module and to test the robustness of the proposed policy. The simulation also helps to determine the advantage of considering correlation between the demands of items sold in systems as compared to neglecting them in the analysis as explained by Serra [26]. The simulation estimates the following performance measures: number of orders lost, their value, months on hand of inventory for every month simulated and dollar value of inventory for each simulated day.

8.3.1 Validation

The optimization model provides the right mix of products that should be available on the floor. To validate these results, the levels were simulated 50 times over two years, 2007 and 2008, and then compared with the projected results from the optimization.

Figure 8-4 shows the losses made for different optimized inventory levels as predicted from the optimization and the simulation, versus the inventory months on hand.

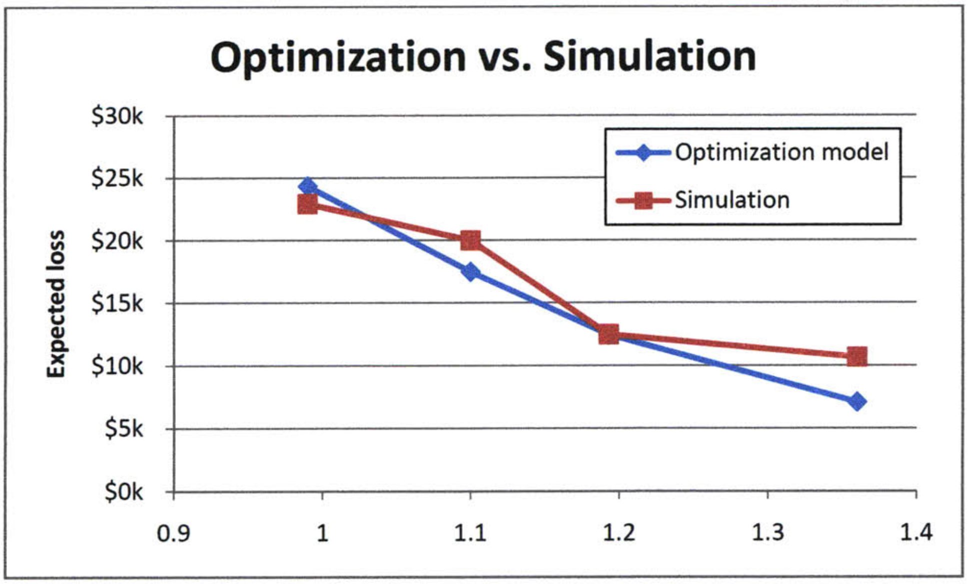

Figure 8-4 - Comparison between theoretical and simulated loss for different solutions of the proposed policy

As it can be seen in figure 8-4, there is a small difference between the performance expected from the optimization model and the simulated one. This is because the optimization is based on the normal assumption, and because the simulation involves random sampling. However, the two graphs show a similar behavior and the difference looks relatively small, supporting the correctness of the optimization model.

This curve led to the selection of a solution providing an average inventory level of 1.2 months on hand, as described in section 8.2.

8.3.2 Robustness analysis

By running the proposed inventory levels over statistical demand, the robustness of the proposed policy can be tested, as described by [26]. The statistical demand is generated using the distribution of demand of each system and item over the previous two years. In the following example, the simulation is run 50 times for seven different values of shift in demand. The shift in demand, however, is not taken into account in calculating the proposed inventory levels. Figure 8-5 depicts the average inventory months on hand versus the shift in demand.

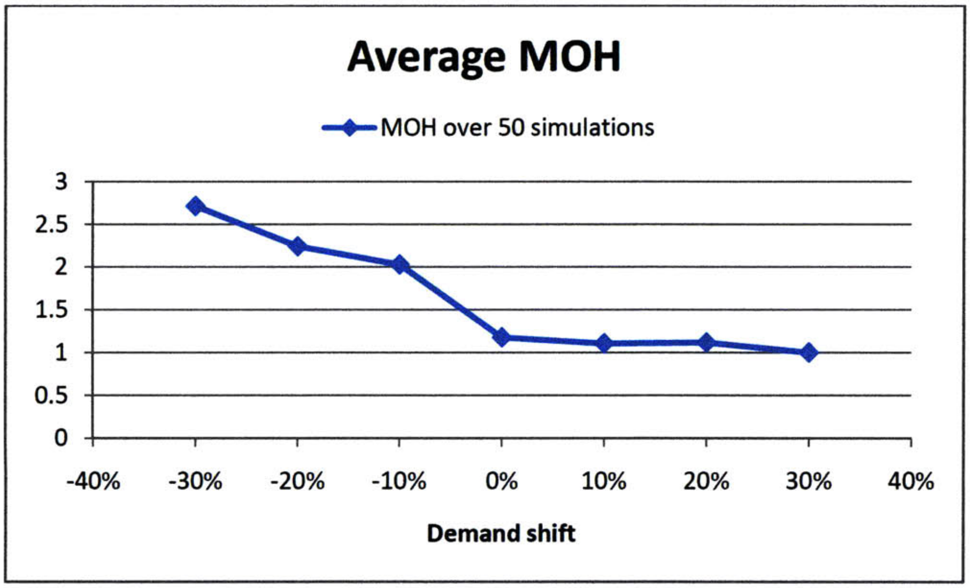

Figure 8-5 - Simulated average MOH vs. demand shift

As the demand decreases the proposed policy shows a steep increase in the MOH (above the limit of 2), while, when there is an increase in the volumes, the months on hand remain substantially stable but there is a considerable increase in the lost sales. This suggests the need for the inventory planner at Instron to update the control parameters as soon as a shift in the demand is detected, using the provided tools.

9. Recommendations

9.1 Introduction

As showed in section 8.2, the optimized control parameters result in a decrease of 35% in the inventory MOH. Moreover, it is estimated that extending the optimization to all the accessories in the Configuration Department would reduce the MOH by a similar percentage. Finally, as mentioned in section 8.1, the raw materials inventory policy provided would cut the parts inventory value on hand by 30% (or even more if shorter lead times are agreed with suppliers).

This represents a substantial motivation to extensively use the software provided, which allows computing the replenishment parameters for all the Instron accessories both at the finished goods and part levels, and integrate it into the Manufacturing Department procedures.

The following recommendations are made to the Instron workers in order to properly implement the proposed policy and allow improvements in the future:

- Compute the inventory levels for the raw parts using the proposed tool as frequently as possible
- Compute the inventory levels for the finished goods using the proposed tool as frequently as possible
- Keep the data on IBS updated as the accuracy of the solutions depend on the quality of available data
- Keep track of the lead times for both raw parts and finished goods
- Use the provided tool to evaluate the benefits of negotiating better lead times from the suppliers

9.2 Discussion

9.2.1 Updating inventory levels

In order to guarantee that the optimal mix of accessories is on the shelves, the inventory planners of the Configuration Department should periodically update the proposed inventory control framework using the most recent sales records available. The computation of the control parameters can be performed with the provided software.

The rapid changes that can occur in the demand, in fact, dictate the need to update the replenishment quantities as frequently as possible. On the other hand, changing the parameters implies a cost in terms of time: the time required to gather the data, run the executable file and insert the new values in IBS. This might imply negotiating new quantities with the suppliers, when agreements exist. Since it is common practice at Instron to update the IBS records at the beginning of every quarter, there is the opportunity to combine these operations and perform the computation every quarter, in time for the data of last quarter to be fully available.

A further decision to be taken by the software operator concerns the quantity of sales data to include in the analysis, for the statistical characterization of the demand and the computation of the Virtual Profit. One year is the minimum time interval that should be considered to properly estimate the variations. As the considered time period increases, the computation time increases as well. Moreover, since there is continuous variation in the product list and in the market, including older data in the analysis implies greater differences between the historical data and the current situation.

In order to minimize the run time and achieve accurate results, the sales records of the last four quarters should be used. As an example, if the analysis is performed in July, the planner should collect the data for the third and fourth quarters of the previous year and for the first and second quarter of the current year.

9.2.2 Shift in demand

As mentioned in Chapter 1, historical sales are used to estimate the future demand. While it is reasonable to assume that the relationships among products (the correlation) and the variations in the demands resemble the ones of the previous year, shifts in the average volumes can occur from one year to another. When a forecast of the shift is available, it should be entered in the command shell of the software, which is able to take this factor into consideration and to provide control parameters that fit the actual situation.

9.2.3 Dividing the analysis

In order for the information involved to be easily managed, the control parameters should not be optimized for all the items at the same time. In fact, because IBS does not currently provide all the quantities needed for the analysis, a manual integration of data is required. For example, the operator has to manually enter lead times for the items considered when not available and check for the accuracy of other parameters, such as unit costs and lot sizes, when unexpected results are detected. Moreover, the optimization of the part level replenishment quantities involves downloading the bill of materials for all the considered products and the complexity of this operation increases with the number of products. Therefore the items should be divided into groups sized so that the operator is comfortable with their management.

The division of the analysis in groups of items allows focusing on the accuracy of the inputted data which is critical for the correct performance of provided software. As an example, the inaccuracy of the lead times data provided by IBS can lead to store inadequate quantity of items.

Similarly, even if the simulation would be a closer representation of the factory floor since more items will be simulated, the run time would become large and the results difficult to interpret.

9.2.4 Lead times accuracy and negotiation

As demonstrated in section 8.1, the correct estimation of the replenishment lead times could lead to a saving of 30% in terms of VOH.

This suggests the need to improve the recording criterion for this type of data, which is currently based on many criteria. For some items that are on Kanban and for the parts that come from Binghamton (another Instron facility) the values of the lead times are known. However, for the majority of the items the lead time corresponds to the maximum lead time that can be tolerated from the supplier. As the cost and the yearly volume of one item increase, the less quantity can be stored for that item and the less time the company can wait for the supply to arrive. Also regarding the finished goods levels, lead times are missing on IBS for the parts assembled or reworked in the Norwood facility. For these parts, in fact, while setup time and run time are usually available, the time that elapses between the arrival of the order and the moment the product is ready is not recorded. The latter, however, is necessary for the computation of the optimal inventory levels.

Sufficiently accurate values can be obtained by using a new recording procedure and integrating it into IBS. Whenever an order is placed to the supplier, the purchasing agent should register the date and the supplier code, assigning a unique code to this record. The same identification number should be used in the receiving area to register the arrival date as soon as the order gets to the Norwood facility. In this way, by comparing the records with the same identification numbers, it is possible to track the lead times for all the items and suppliers so that they can be used in the computation of the inventory control parameters. When variability is present, the statistical distributions of the lead times can be evaluated. The availability of this type of data would potentially allow an extension of the optimization tools which consider stochastic lead times, as described in section 7.1.

As also showed in the raw materials control, a more drastic drop in the VOH can by achieved by negotiating shorter lead times with the suppliers. Whenever negotiation is possible, the supply chain planners should use the provided tool to evaluate the possible benefits of changing the lead times. In particular, they can compare the decrease in inventory value on hand with the eventual increase in purchasing cost.

9.2.5 Product categories

The category of a finished good (face, grip, fixture, etc.) is not stored by the IT system. However, as showed in chapter 6, the customer expectations differ for items belonging to different categories, and this record becomes important for the optimization tool. Right now such information can be found in the product catalog and in many other sources. However, keeping an updatable database or excel file with all the products divided by categories would help to easily identify this information and decrease the time necessary to gather the data needed for the finished goods optimization program.

9.2.6 Warning messages

For what concerns the information accuracy, the operator should take advantage of the warning messages displayed by the programs provided when unexpected results are detected. The user is provided with detailed instructions to follow when such events occur, and with the operating procedure for the calculation of the inventory control parameters. The detailed instructions are provided to the user with the software, and are not shown in this work.

9.2.7 New products and substitutions

Whenever new products are released and their replenishment quantities have to be calculated, the operator should provide a table containing information about the new items. Two cases can be considered:

- If the new products directly substitute one or more items in the product list, those item should be indicated as well as the fraction of demand of the old product that would converge into the new one. This allows the program to estimate the Virtual Profit and the statistical parameters of the new products demands based on the old sales data.

- If the new products are added to the product list and no old item is substituted, no historical sales data can be used to estimate the Virtual Profit, and the control parameters should be evaluated based on the simple QR model, without considering the correlation among the new items and the rest of the product list. In this case the operator is asked to provide a forecast of the future sales. This data is used to estimate mean value and standard deviation of the demand, and the z-factors are set by default to a high value which is not necessarily the optimal one, which cannot be estimated without knowing the Virtual Profit, but matches the need for the company to provide a high service level when the new items are introduced to the market.

9.2.8 Selecting the best solution

The final step of the computation of the control parameters involves the selection of the desired solution. Different solutions are provided, each one involving a different value of average MOH, and the operator is asked to choose one of them. A graph, similar to the one showed in figure 9-1, is displayed in order to aid the selection. For all the different solutions, the loss of sales profits and the MOH are plotted in the same graph and, as described in Facelli [27], the higher is the MOH, the smaller loss is achieved.

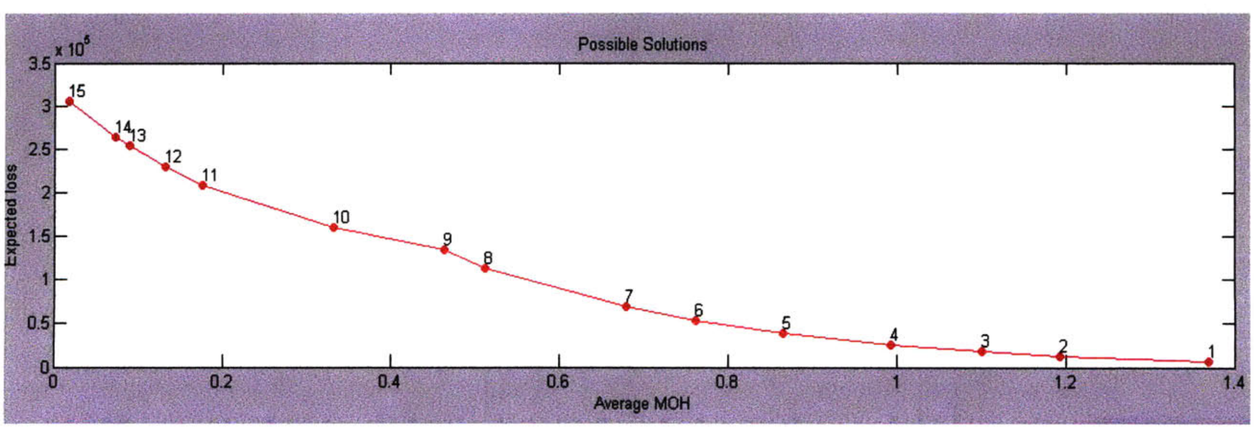

Figure 9-1 – Expected loss from sales vs. average inventory VOH for different solutions of the optimization.

When making this decision, the operator should consider that the displayed MOH is an average value and may fluctuate depending of the variability of the sales volumes. Because the Instron demand is subject to consistent fluctuations, the operator should not choose a value close to 2 MOH, which is the maximum value allowed at Instron. At the same time a small loss from sales should be achieved. This curve usually shows a flat tail, where for a little increase in the inventory cost only a little portion of sales is redeemed. The starting point of the flat tail can be considered a satisfactory solution.

9.2.9 Using and adjusting the recommended quantities

The output of this computation is a list of recommended minimum quantities and reorder quantities, which are the parameters used to build the Kanban cards. While the reorder quantity coincides with Q in the QR model, the minimum quantity is $R+1$. The reason for this is that the minimum quantity indicates the number of items contained in a bag; when the bag is opened to take one part the level R is reached and the order is placed.

At this point, the operator has the chance to modify the proposed quantities if constraints are present. For instance, constraints on the lot sizes exist. In addition, some items have to be ordered or assembled in lots that are multiples of some predetermined quantity. After the quantities are updated according to these constraints, a sensitivity analysis for the finished goods should be performed in order to evaluate the increase in the costs. The quantities can be directly modified in the Excel spreadsheet provided as output of the optimization tool, and the updated values of the theoretical MOH and VOH are showed. These quantities can be compared with the proposed ones and the choice must be taken accordingly.

A simulation can also be performed to observe the changes introduced by the adjusted quantities on the lost sales, value on hand and months on hand.

10. Future work

As discussed in the Results and Discussion section, Instron has potential for improving its operations management. The result of this work is reducing wastes in the inventory management. Some topics from this research, which can be further explored, are:

10.1 Lead time variability

Lead time variability is critical to every inventory policy. Variation in lead time can lead to unexpected stock outs or surges in inventory leading to increased costs and unsatisfied customers. This issue can be taken into account if the variation in lead time is known. If Instron Corporation keeps track of lead times as described in the recommendations section, the variability can be recorded and implemented inside the replenishment policy.

10.2 Manufacturing constraints

Manufacturing constraints are essential on a factory floor since mostly limited work force is available to accomplish tasks. Orders sometimes need to be rescheduled, or in the worst case lost, if manufacturing constraints and pending commitments are not taken into consideration while promising a lead time to a customer. Thus, while determining the finished goods and part levels, it is important to consider the manufacturing constraints since if these are not considered, unrealistic levels will be obtained. At the same time, the initial analysis has revealed that most of the manufacturing constraints are both independent and difficult to quantify.

Currently, final finished good levels are checked and compared by the inventory planning team before implementing. Also, the lead times have been increased to account for manufacturing constraints (Facelli [27]). However, the optimum method to implement this would be to consider the constraints inside the optimization and simulation itself. This will make the new inventory levels faster to implement and easily reusable.

10.3 Include back orders in the simulation

As discussed in Chugh [28], simulation has been developed on a simplified model of the manufacturing floor. Back orders have not been considered in the simulation and immediate order execution is being done. However, in reality, back orders will cause the orders to wait longer than required. Implementing back orders in the simulation is a complex process and needs the creation of a new database to keep track of them. Also, some orders are unexpectedly delayed due to incomplete payments, quality audits, etc. A more accurate picture can be obtained if back orders and manufacturing time is considered inside the simulation.

10.4 Include part level into the simulation

Currently the simulation tool only considers the finished goods level. The part level inventory has been determined directly under the condition that it has to be available with a very high probability whenever the finished goods need to be prepared. This, however, is an approximation and there is a miniscule probability that an order cannot be satisfied if a part level inventory is not available. Thus, it is required that a simulation be built which starts from the part level inventory, develops finished goods and finally executes the orders. This simulation will be a more accurate representation of the factory floor.

10.5 QR policy using Poisson distributed demand

As shown by Serra, Instron's monthly demand for frames can be better approximated with a Poisson distribution [26]. The assumption of normally distributed and continuous demand fits well the reality if the average demand is large enough. However for many products at Instron the sales volume is limited and it might then be interesting to perform a similar analysis with a QR policy assuming Poisson distributed demand. An in depth study can provide detailed results on whether changing the demand distribution can lead to increased profits.

10.6 Category-wise Optimization

Optimization is a complex process to run every time. It gives the service levels for each item such that an optimal mix is obtained. However, having different service level for every item can lead to confusion while undergoing policy revisions and corrections. Currently, the factory floor operates on dividing the products into categories based on values having very high service levels for each item in every category.

An optimization framework can be implemented which can present discrete service levels for such categories. The benefit of using such a method is that not only will the manufacturing planners will have easy control and understanding over such a system but, also that the correct mix of products will be available while working within the same framework. However, this solution would be less optimal than the solution proposed in this work and its implementation may still be complex.

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Appendix A – Customer expectation survey

The following is extracted from the customer expectation survey discussed in chapter 6.

Section 1_OTC Grips

A. A customer orders a grip by OTC. If the grip is not in stock, what is the maximum waiting time that 100% of the customers will accept?

O 1 days	O 4 days	O 2 week
O 2 days	O 1 week	O Other:

B. If the grip is not in stock, what is the waiting time that would cause you to lose about 20% of the orders (not more)?

O 1 week	O 3 weeks	O 5 weeks	O 7 weeks
O 2 weeks	O 4 weeks	O 6 weeks	O Other:

C. If the grip is not in stock, what is the minimum value of the waiting time that the customers will not accept

O 4 weeks	O 6 weeks	O 8 weeks	O 10 weeks
O 5 weeks	O 7 weeks	O 9 weeks	O Other:

D. Are your answers valid for all the grips or is there any particular grip / grips for which the customers will have different expectations?
- o Same for all
- o No, ex: ______________

E. How confident are you of your answers for this section?
- o 5 – Very confident
- o 4
- o 3
- o 2
- o 1 – I'm not confident for this category

F. Do you have any other comments about this product category?

Appendix B – MATLAB code

The following is the code used to calculate the statistics of the raw materials usage, as discussed in chapter 7.

- *File "GripCellUsage.m"*

```
function GripCellUsage

% Code to deal with part level inventory for the "80" Grips

clear all
close all
clc;

%Definitions
COL.ALevel=4;
COL.ItemNumber=6;
COL.OrderQty=7;
COL.QtyShipped=8;
COL.StdCost=9;
COL.ExtNetPrice=12;
COL.OrderEntry=13;
COL.PostCode=14;

%Importing data
[num, txt, raw] = xlsread('partscorrespondance.xls', 'table');

% building 2 arrays (grips and parts) and 1 matrix for the associations and
% quantities
quantities=zeros(size(raw,1)-1,size(raw,2)-2);
for i=2:size(raw,1)
    parts{i-1,1}=raw{i,1};
    for j=3:size(raw,2)
        quantities(i-1,j-2)=num(i-1,j-2);
    end
end
for j=3:size(raw,2)
    grips{j-2,1}=raw{1,j};
end

%Importing new products
[num_newprod, txt_newprod, raw_newprod] = xlsread('Newproducts.xls',
'Substitutions');
for i=2:size(raw_newprod,1)
    if isequalwithequalnans(raw_newprod(i,1),{NaN})
        o=100; break
```

```
    end
    old_prod(i-1)=raw_newprod(i,1);
    prob(i-1)=raw_newprod{i,2};
    new_prod(i-1)=raw_newprod(i,3);
    new_prod2(i-1)=raw_newprod(i,6);
end

%Importing demand shifts
[num_shift, txt_shift, raw_shift] = xlsread('Newproducts.xls',
'DemandShift');
for i=2:size(raw_shift,1)
    if isequalwithequalnans(raw_shift(i,1),{NaN})
        break
    end
    shifted_prod(i-1)=raw_shift(i,1);
    shift_amount(i-1)=raw_shift(i,2);
end

clear num_shift txt_shift raw_shift num_newprod txt_newprod raw_newprod num
txt raw

N=input('How many files with orders will you insert?\n>: ');

%Import items order files
%The function "ImportData" is described in Serra [26]
%It asks the user to insert the sales records and removes unnecessary
%information from them
AllData=[];
for i=1:N
    [a,b,data]=ImportData('orders');
    AllData=vertcat(AllData,data);
end
clear a b;

% Ask for the shift in the demand
fprintf('\nInsert the estimated percentage shift in the demand, relative to
the inserted data ' );
fprintf('\n(example: if the demand increases by 50%% insert 50)\n');
fprintf('\n(example: if no shift is expected insert 0)\n');
big_shift=input('\n>: ');
big_shift=big_shift/100+1;

%Translate grip orders into parts orders
k=1;
PartsOrders=[];
GripsOrders=[];
SIZE=size(AllData,1);
for i=1:SIZE
    % show progress
    if mod(i,round(SIZE/100))==0 clc; fprintf('Processing
orders:%d%%\n',round(100*i/SIZE));
    end
    % select useful lines
    for j=1:size(grips,1)
        found=0;
        if (isequal(AllData{i,COL.ItemNumber},grips{j,1}))
```

```
            % a grip order is found.
            found=1;
            m=j;

            AllData{i,COL.QtyShipped}=big_shift*AllData{i,COL.QtyShipped};
            AllData{i,COL.OrderQty}=big_shift*AllData{i,COL.OrderQty};

            %check if it is a product with demand shift
            if ~isempty(shifted_prod)
                for l=1:size(shifted_prod,2)
                    if (isequal(AllData{i,COL.ItemNumber},shifted_prod{l}))

AllData{i,COL.QtyShipped}=shift_amount{l}*AllData{i,COL.QtyShipped};

AllData{i,COL.OrderQty}=shift_amount{l}*AllData{i,COL.OrderQty};
                    end
                end
            end

            .
            % check if the product was substituted
            if ~isempty(old_prod)
                for l=1:size(old_prod,2)
                    if (isequal(AllData{i,COL.ItemNumber},old_prod{l}))
                        found=1;
                        % the product is one of the obsoleted ones
                        dice=rand();
                        if dice<=prob(l)
                            AllData{i,COL.ItemNumber}=new_prod{l};
                        else AllData{i,COL.ItemNumber}=new_prod2{l};
                        end
                        for n=1:size(grips,1)
                            if
(isequal(AllData{i,COL.ItemNumber},grips{n,1}))
                                m=n;
                                break;
                            end
                        end
                    end
                end
            end

            GripsOrders=vertcat(GripsOrders, AllData(i,:));
            % ItemsOrders(k,:)=AllData(i,:); %this is just for debugging and
can be deleted
            % then generate Items Orders
            for p=1:length(parts)
                if quantities(p,m)>0
                    %create item order line
                    Line=AllData(i,:);
                    Line{1,COL.ItemNumber}=parts{p};

Line{1,COL.QtyShipped}=Line{1,COL.QtyShipped}*quantities(p,m);

Line{1,COL.OrderQty}=Line{1,COL.OrderQty}*quantities(p,m);
                    %copy item order line
```

```
                    PartsOrders=vertcat(PartsOrders, Line);
                end
                k=k+1;
            end
        end
        if found==1 break;
        end

    end
end

%now the file orders.xls should be similar to the old one, and we can
calculate mu and sigma in the same way

% save('PartsOrders.mat', 'PartsOrders', 'parts', 'GripsOrders', 'grips');
clc;
fprintf('Orders processed successfully\nProcessing statistics...\n\n');



% Part Level and grips statistical analysis
% clear all
% load PartsOrders.mat

[FirstDay, LastDay] = finddays(PartsOrders);

[Pindex, PdailyDemand] = dailyStat(PartsOrders, parts, FirstDay, LastDay);
[Gindex, GdailyDemand] = dailyStat(GripsOrders, grips, FirstDay, LastDay);
% clear PartsOrders GripsOrders

PLDailyStDev=std(PdailyDemand,0,2);
PLDailyAvg=mean(PdailyDemand,2);
GDailyAvg=mean(GdailyDemand,2);
GMonthlyAvg=GDailyAvg.*365/12;

XLSWRITE('stats.xls',{'Grip #','daily usage','monthly usage'},'Grips
usage','A1:C1');
XLSWRITE('stats.xls',{'Part #','daily usage','daily st dev'},'Parts
usage','A1:C1');
XLSWRITE('stats.xls',grips,'Grips usage','A2');
XLSWRITE('stats.xls',GDailyAvg,'Grips usage','B2');
XLSWRITE('stats.xls',GMonthlyAvg,'Grips usage','C2');
XLSWRITE('stats.xls',parts,'Parts usage','A2');
XLSWRITE('stats.xls',PLDailyAvg,'Parts usage','B2');
XLSWRITE('stats.xls',PLDailyStDev,'Parts usage','C2');

% save('PLDailyStDev', 'PLDailyAvg', 'GDailyAvg');
% clc;
fprintf('Statistics calculated successfully\n');
```

- *Function "findDays.m"*

```
function [FirstDay, LastDay] = finddays(matrix)

% create array with dates in numbers
for i=1:length(matrix(:,13)) date(i)=matrix{i,13}; end
% find initial and final month
m=min(date);
M=max(date);
% find last day of last month in the orders
D=datevec(M);
D(3)=1;
N1=addtodate(M,1,'month');
D1=datevec(N1);
D1(3)=1;
daysinlastmonth=datenum(D1)-datenum(D);
D(3)=daysinlastmonth;
%find first day of first month in the orders
d=datevec(m);
d(3)=1;

FirstDay=datenum(d);
LastDay=datenum(D);
```

- *Function "dailyStats.m"*

```
function [index, dailyDemand] = dailyStat(Matrix, index, f, l)

%Parameters
%indicate the column number in the spreadsheet
COL.ItemNumber=6;
COL.OrderQty=7;
COL.QtyShipped=8;
COL.OrderEntry=13;

%Create an item index
for i=1:size(Matrix,1)
    indexP(i,1)=Matrix(i,COL.ItemNumber);
end

% indexP=Matrix(:,COL.ItemNumber); %take Regular column
k=0;
Ind=length(index);
if isempty(index)
    k=1;
    index=indexP(1,1);
end
```

```
for i=1:length(indexP)
    for j=1:Ind+k
        flag=0;
        if (isequal(index(j,1),indexP(i,1)))
            flag=1;
            break
        end
    end;
    if (flag==0)
        k=k+1;
        index(Ind+k,1)=indexP(i,1);
    end;
end;
clear indexP

M=size(Matrix,1);

%store the daily demand for every item
dailyDemand=zeros(length(index),l+1-f);

for j=1:M
    %this is for robustness to strange data
    if iscell(Matrix{j,COL.QtyShipped})
        Matrix{j,COL.QtyShipped}=Matrix{j,COL.QtyShipped}{1};
    end
    for i=1:length(index)
        if strcmp(index{i},Matrix{j,COL.ItemNumber})
            dailyDemand(i,Matrix{j,COL.OrderEntry}-
f+1)=dailyDemand(i,Matrix{j,COL.OrderEntry}-
f+1)+(Matrix{j,COL.QtyShipped}+Matrix{j,COL.OrderQty});
        end
    end
end
end
```